DOCTORAL THESIS

Innovative Energy Services based on Behavioural-Reflective-Attributes and Intelligent Recommendation Systems

Abiodun Emmanuel Onile

TALLINNA TEHNIKAÜLIKOOL
TALLINN UNIVERSITY OF TECHNOLOGY
TALLINN 2024

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DOCTORAL THESIS
62/2024

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ABIODUN EMMANUEL ONILE

TALTECH PRESS

TALLINN UNIVERSITY OF TECHNOLOGY
School of Information Technologies
Department of Software Science

The dissertation was accepted for the defence of the degree of Doctor of Philosophy (Software Science) on the 14th of October, 2024

Supervisor: Professor Juri Belikov,
Department of Software Science, School of Information Technologies,
Tallinn University of Technology
Tallinn, Estonia

Co-supervisor: Professor Eduard Petlenkov,
Department of Computer Systems, School of Information Technologies,
Tallinn University of Technology
Tallinn, Estonia

Opponents: Professor Bo Norredaard Jorgensen,
SDU Center for Energy Informatics University of Southern Denmark,
Odense, Denmark

Professor Lucio de Paolis,
Department of Engineering for Innovation University of Salento,
Lecce, Italy

Defence of the thesis: 12th of November 2024, Tallinn

Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology, has not been submitted for any academic degree elsewhere.

Abiodun Emmanuel ONILE ______________________
signature

ISSN 2585-6898 (publication)
ISBN 978-9916-80-218-2 (publication)
ISSN 2585-6901 (PDF)
ISBN 978-9916-80-219-9 (PDF)
DOI https://doi.org/10.23658/taltech.62/2024
Printed by Koopia Niini & Rauam

Onile, A. E. (2024). *Innovative Energy Services based on Behavioural-Reflective-Attributes and Intelligent Recommendation Systems* [TalTech Press]. https://doi.org/10.23658/taltech.62/2024

TALLINNA TEHNIKAÜLIKOOL
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62/2024

Arukatel soovitussüsteemidel põhinevad uuenduslikud energiateenused

ABIODUN EMMANUEL ONILE

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Contents

List of Publications

The present Ph.D. thesis is based on the following publications that are referred to in the following text.

I A. E. Onile, J. Belikov, and Y. Levron. Innovative energy services for behavioral-reflective attributes and intelligent recommender system. *In Proceedings of 2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe) – 10th International conference of IEEE PES ISGT Europe Conference*, *Virtual*, *The Hague*, *Netherlands*, *2020*, 1(1):1–7, 2020

II A. Navon, R. Machlev, D. Carmon, A. E. Onile, J. Belikov, and Y. Levron. Effects of the COVID-19 pandemic on energy systems and electric power grids—a review of the challenges ahead. *Energies*, 14(4), 2021

III A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. A comparative study on graph-based ranking algorithms for consumer-oriented demand side management. In *Proceedings of 2021 IEEE Madrid PowerTech – 14th IEEE PowerTech*, pages 1–6, 2021

IV A. E. Onile, R. Machlev, E. Petlenkov, Y. Levron, and J. Belikov. Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. *Energy Reports*, 7:997–1015, 2021

V A. E. Onile, J. Belikov, Y. Levron, and E. Petlenkov. Energy efficient behavior modeling for demand side recommender system in solar microgrid applications using multi-agent reinforcement learning model. *Sustainable Cities and Society*, 90:104392, 2023

VI A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Applications of digital twins for demand side recommendation scheme with consumer comfort constraint. In *Proceedings of IEEE PES ISGT Europe 2023 (ISGT Europe 2023) – 13th International conference of IEEE PES ISGT Europe Conference*, 2023

VII A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Emerging role of Industry 5.0 digital twins in demand response electricity market and applications. In *Proceedings of IEEE PES ISGT Europe 2023 (ISGT Europe 2023) – 13th International conference of IEEE PES ISGT Europe Conference*, 2023

VIII A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Leveraging digital twins and demand side recommender chatbot for optimizing smart grid energy efficiency. In *Proceedings of 2023 IEEE PES Innovative Smart Grid Technologies - Asia (ISGT Asia) – 13th IEEE PES Innovative Smart Grid Technologies*, *Asia conference*, pages 1–5, 2023

IX K. Nosrati, S. Alsaleh, A. Tepljakov, E. Petlenkov, A. E. Onile, V. Škiparev, and J. Belikov. Extended reality in power distribution grid: applications and future trends. In *Proceedings of 27th International Conference on Electricity Distribution (CIRED 2023)*, volume 2023, pages 3615–3619, 2023

Author's Contributions to the Publications

The author's contributions to the the papers in the thesis are described as follows:

I In Paper I, I was the lead author and first author. I wrote the simulation program, carried out the simulations and the analysis of the results, prepared the figures, and wrote the manuscript.

II In Paper II, the problems associated with the effect of market shocks (i.e. COVID-19) on the energy systems were considered. I was responsible for curating the literature data and writing the manuscript.

III In Paper III, the author's contributions can be seen in the design of graph-based ranking models for estimating the behaviour of individual electricity asset. The graph-based model designed was tailored to improve the behaviour scoring outcome without initial requirements for training.

IV In Paper IV, the author of the thesis assumed the collective role of conception and design of the idea and the analysis, and interpretation of data. In this study, as the lead author, I was also responsible for drafting the article and presenting the state-of-the-art analysis of the topic, which involves the use of DT for a demand-side management solution.

V In Paper V, as the lead author and first author, I developed a multi-agent reinforcement learning platform for alleviating end-consumers discomfort while adopting a demand-response solution.

VI In Paper VI, I was the lead author. The study focused on the use of digital twins and multiagent reinforcement learning control for the introduction of consumer comfort constraints in a demand-side recommendation scheme.

VII In Paper VII, I was the lead author and I contributed by developing digital twins of an individual electricity asset targeted at asset-level participation in the demand-response electricity market. Specifically, the study focused on the emerging role of Industry 5.0 digital twins in demand-response applications and the electricity market.

VIII In Paper VIII, a study on leveraging digital twins and a demand-side recommender chatbot for optimizing smart grid energy efficiency was developed. Particularly, the implementation adopted the use of the engagement index (EI) metric for formalising consumer engagements. The author of the thesis is the lead author and contributed to the conceptualization, methodology, writing, and preparation of the original draft.

IX In Paper IX, a study on the application and future trend of an extended reality application in the power distribution grid was presented. The implementation section involves the use of demand-side recommendation services. This section was designed and implemented by me.

Abbreviations

AI	Artificial intelligence
AMI	Advanced measuring infrastructure
ANN	Artificial neural network
BESS	Battery energy storage system
BAU	Business as usual
BTU	British thermal unit
CCI	Consumer comfort index
CFL	Compact fluorescent lamp
CGC	Compagnie générale de chauffe
CO	Combinatorial optimization
CTR	Click-through rates
CPU	Central processing unit
COVID-19	Coronavirus disease
DL	Deep learning
DT	Digital twin
DR	Demand response
DSM	Demand side management
dSOC	Discrete state space of battery charge
DSS	Decision support systems
DERs	Distributed energy resources
EE	Energy efficiency
EER	Energy efficiency ratio
EI	Engagement index
EPC	Energy performance contracting
EV	Electric vehicle
FD	Feedback delay
ESCOs	Energy service companies
GBDT	Gradient boosting decision tree
GHG	Green house gas
GPT-3	Generative pre-trained transformer 3
GPU	Graphics processing unit
HITS	Hyperlink-induced topic search
HVAC	Heating, ventilation, and air conditioning
HPO	Hyperparameter optimization
ICT	Information and communication technology
IES	Innovative energy services
IoT	Internet of things
ISOs	Independent system operators
LED	Light-emitting diode
Li-ion	Lithium iron
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MARLISA	Multi-agent reinforcement learning with iterative selective actions
MC	Markov chain
MDP	Markov decision process
ML	Machine learning
MSE	Mean square error
NAR	Nonlinear autoregressive model

NILM	Non-intrusive load monitoring
ODE	Ordinary differential equation
PCA	Principal component analysis
PGML	Physics-guided machine learning
PM	Particulate matter
PMU	Phasor measurement unit
PRC	Precision-recall curve
PSO	Particle swarm optimization
PV	Solar photovoltaic
REDD	Reference energy disaggregation dataset
ReLU	Rectified linear unit
RET	Renewable energy technologies
RES	Renewable energy sources
R&D	Research and development
RL	Reinforcement learning
RNN	Recurrent neural network
RMSE	Root mean squared error
R^2	R-squared
SAC	Soft actor-critic
SDGs	Sustainable development goals
SOC	State of charge
TPU	Tensor processing units
VR	Virtual reality
VS	Visual simulation
VRE	Variable renewable energy
XR	Extended reality
ZEB	Zero-energy buildings

Symbols

ϕ	Solar irradiation
φ	Non-linear transformation function
η	PV conservation efficiency
π_θ	Policy
$\mathbb{E}_{at}$	Expectation term
γ_m	Loss function

1 Introduction

Energy consumption in recent decades has been on the rise, and this is cognate to electricity serving as a reliable substitute to oil and gas, serving as both a primary and a secondary energy source [36]. This situation projects the electricity sector as the leading contributor to greenhouse gas (GHG) [110].

With rising energy consumption and growing environmental concerns, there's a push to encourage consumers to adopt energy-efficient practices [91]. However, challenges arise due to consumers' shortcomings in implementing these measures. Often, consumers show less vigilance towards energy savings, and there is limited groundwork for comprehending consumers' energy behaviours [11]. Additionally, consumers lack technical expertise, economic resources, and time, which are crucial for a comprehensive evaluation of energy efficiency measures. For instance, consumer energy behaviour involves abstract concepts (such as W and kWh), making it less personally relevant and challenging for the majority for end-consumers to grasp [154]. The traditional electricity grid falls short in meeting the escalating demand and inadequately addresses essential requirements for demand-response (DR) programs [81]. The traditional DR approach of using the services of energy service contractors such as energy service companies (ESCOs) has been considered i) less intuitive, ii) less scalable [173] because the distributed nature of the residential sector obstructs the adoption of energy performance contracting (EPC) [201], and iii) more error prone [120, 143, 138] from the end-user perspective, thus preventing the successful delivery of energy services [128]. To meet the ambitious decarbonization goals set for 2030 and 2050, the residential sector in the EU needs to actively contribute to the solution [9]. However, the extended period required for returns on investments makes the services offered by ESCOs financially unappealing to numerous building occupants. This scenario impedes the significant potential for energy conservation in a sector accountable for nearly half of Europe's energy usage.

It is widely acknowledged that what are termed "energy" services rely on various products, infrastructure, and inputs beyond just energy-consuming devices, including factors such as labour [118]. Consequently, other factors such as problems associated with end-user disengagement and the widening "knowledge action gap" [41] in relation to energy-efficiency adoption are worthy of examination. A similar problem is end-consumers' comfort-related issues that prevent the adoption of DR schemes. Notably, certain activities place considerable demands on consumers, leading some individuals to be reluctant in per-forming specified energy-saving tasks. Depending on individual circumstances, some con-sumers may opt to shift their energy usage from peak hours, while others might have commitments preventing them from altering their energy usage schedules [189]. Hence, there's a necessity for aligning the potential energy-saving impact of an action with a consumer's willingness to execute the recommended action. While energy-efficient recommendations have shown significant enhancements in consumer energy behaviour [143, 138], certain studies suggest implementing a direct human feedback mechanism to address discomfort as an objective measure. This mechanism allows consumers to manually override recommendations and prioritize their personal preferences [168]. While this approach promotes comfort, it further worsen the problem of the 'knowledge-action gap' [136]. A proposed solution that employs strategies that work together in saving energy while equally ensuring end-consumers' comfort can generate a combined or cooperative effect, enhancing both comfort and energy efficiency for end-consumers. Consequently, this could increase their enthusiasm and engagement, thus overcoming the obstacles to adoption [91].

During the past two decades, one expectation has been that the challenges related to grid electrification could be resolved by transitioning to a decentralized approach for electrification, centred around renewable energy technologies [85]. Distributed generation technologies such as solar photovoltaic (PV) and battery energy storage systems (BESS) are highlighted as appealing alternatives for energy management. While the growing integration of transient renewable energy sources offers promising solutions, it also introduces emerging stability issues for the electricity grid. The transitional characteristics of renewable energy sources (RES), such as frequency and voltage instability, however, pose distinct challenges during integration. Renewable energy sources often face challenges related to frequency and voltage instability, primarily due to their low inertial and generating capacity [162]. Consequently, multiple unresolved issues persist, hindering the seamless deployment of RES [168]. Another issue arises with energy aggregators, which, originally advocate for energy management solutions, now tend towards monopolistic practices to enhance profits due to the transitional nature of RES [33, 176]. Aggregators are recognized as pivotal facilitators enabling the integration of distributed energy resources (DERs) into electricity networks and the provision of demand-response (DR) services on a larger scale [34]. They play a vital role in fostering the development of sustainable grids and are often positioned at the forefront of advocating for DER adoption. These entities serve as crucial intermediaries linking Transmission System Operators (TSOs) or Independent System Operators (ISOs) and utilities to fleets of DERs, delivering various services, including demand response [15]. However, a notable challenge lies in the fact that system operators/TSOs do not have direct access to the feedback information available to aggregators [15], as aggregators possess strategic control over curtailing generation resources without TSOs being aware, granting them opportunities to manipulate prices. Consequently, the role of DER aggregators as value creators might be transient as the power system progresses into the future [34, 12], wherein technological advancements and regulatory developments are likely to supplant the role of aggregators and overcome the limitations (such as imperfect coordination, aggregators' market monopoly) that currently exist. It is noteworthy that the introduction of improved modelling technologies for RES could help mitigate the issue of stability impact associated with RES.

Accurate representation of the behaviour of grid assets and stakeholders is important and cannot be overemphasized. On 30 January 2020, the World Health Organization officially categorized the 2019 Coronavirus disease (COVID-19) as a global public health emergency. The energy sector promptly and efficiently responded to this declaration. There was a unanimous recognition that ensuring consistent and dependable electricity provision is a vital service. Any disruptions were acknowledged to carry immense consequences that needed to be averted by all means [147]. A notable trend observed is the pandemic's influence on energy consumption behaviours and peak demand. Primarily stemming from government-implemented preventive measures [25], numerous countries experienced a substantial decline in electricity usage within commercial and industrial sectors [23]. This reduction posed several hurdles for electric utilities and system operators. Challenges arose due to irregular consumption patterns, such as elevated voltage levels and imprecise load forecasts. Additionally, there were indirect consequences, including increased shares of renewable energy generation, resulting in challenges such as steep ramp rates and frequency fluctuations. The COVID-19 pandemic is not just a global health emergency; it could mark the onset of a new phase in economic activity, the full implications of which remain uncertain. Within this context, extensive studies have focused on understanding the medium to long-term impacts of the pandemic on the energy sector in recent months. However, despite these endeavors, numerous questions persist regarding the pandemic's lasting effects on power systems. For example, how will it impact the incorporation of renewable energy sources? Should current plans for expanding power systems change in response to COVID-19? What new resources or tools are necessary to aid system operators during global health crises?

Embracing a sustainable development agenda is crucial for moving towards an energy-efficient economy. This requires implementing measures that extend beyond technologies and policies, encompassing innovation aligned with the United Nations' Sustainable Development Goals (SDGs) [73]. The current European Union efficiency drive (art 8) and the future Horizon Europe (cluster 5) programs encourage the development of programs allowing consumers to undergo energy audit and provide incentives for implementing the resulting recommendations. On the contrary, consumers lack the expertise, capital, and time resources to implement the required conservation measures.

Innovative energy services (IES) play a crucial role in addressing the challenges related to energy inefficiency. They aim to assist consumers in transitioning towards actions that promote energy sustainability. Empowered by smart technological solutions, energy consumers can now redefine their role to become more engaged participants in the market. These services enable proactive utilities and digitally adept consumers to establish their presence in the swiftly evolving digital energy ecosystem. While the outlook for energy services seems promising, a considerable portion of consumers remain disconnected or unaware of the opportunities presented to them. This disengagement often stems from a lack of information or concerns about potential complications associated with making changes. The viability of innovative energy services hinges on digitization, empowering consumers and fostering new possibilities. For these services to gain traction in the market, consumers must be informed about them through abundant and dependable guidance [109]. Likewise, digital technologies have made significant strides in recent decades. These advancements enable real-time synchronization and monitoring of the energy system through computerized and virtual world modelling. This modelling is based on data, information, and consumer behaviour [31] [172]. Again, with the rising adoption of smart home technologies in residential spaces and the emergence of substantial data streams enabling a deeper understanding of demand-side dynamics, the increasing prevalence of self-consumption models and energy communities, and the expanding decentralization schemes of the energy system, it becomes evident that there is movement towards developing and implementing innovative energy services. These services aim to empower small residential consumers, transforming them into active participants and equal contributors within evolving energy markets that emphasize their inclusion in smart grid management strategies [9]. Furthermore, gaining a deeper understanding of consumer or electricity asset behaviours is crucial to predicting their energy consumption patterns, a key element in reducing energy usage. Effective energy-related behavioural changes can be facilitated by intelligent recommendations. These recommendation systems offer guidance on various action alternatives, enabling consumers to access services tailored specifically to their needs among a wide array of choices [4].

Recommender systems offer a promising avenue for furthering energy conservation, aiding consumers in maximizing their energy-saving choices and potential. Recommender systems furnish insights into the benefits linked to selecting an alternative action. Their primary aim is to offer tailored suggestions, guiding consumers in a personalized manner towards suitable choices among a vast array of possibilities [4]. This approach, commonly used in electronic commerce industries, provides recommendation tips that assist consumers in conveniently achieving their energy optimization goals. The integration of personalized recommendations into demand-side management (DSM) holds substantial promise for enhancing consumers' energy efficiency. Studies on persuasive technology indicate that technological interventions can aid consumers in their quest for self-improvement. Within the energy sector, tools such as social comparison, feedback mechanisms, and goal setting have effectively influenced consumers' conservation behaviour. Traditional recommendation systems display all available services to consumers, whereas the next-generation systems are anticipated to be comprehensive and adaptable, aligning with consumers' present circumstances without jeopardizing their personal data or privacy, comfort, or end-consumer engagement (i.e. conversational chatbot).

In light of these developments, this thesis presents a framework for IES-based recommender systems. We revisit the key elements and demonstrate their potential to yield more targeted recommendations. In contrast to most current methods centred on utility-driven solutions, our proposition involves a fundamental rethinking—placing consumers at the core by replacing customers with their digital twins. For example, to obtain a thorough assessment of energy inefficiency, we examined the established IES model through the utilization of two major tools/technologies: recreating energy consumer behaviour using hybrid digital twin technology, and implementing a recommendation system to offer actionable insights (details in Section 3 and Section 4). The suggested concept could offer energy-saving alternatives without requiring substantial changes to the consumers' way of life. This could be accomplished by predicting consumer consumption patterns while simultaneously generating the necessary recommendations to optimize energy usage.

Figure 5 describes the schematic layout of the study. Figures 5 and 6 depict the schematic and detailed outline of the suggested method, which commences by gathering data linked to a consumer's energy usage and concludes with tailored suggestions.

The thesis is composed using a compilation of scholarly publications that have undergone peer review. The results/findings obtained in the course of the thesis have been published in scientific journals and conferences. In all, the author has contributed to ten publications related to the creation of an intelligent recommender system tailored for demand-side management (DSM) solutions aimed at consumers. The primary contribution of the scientific publication crafted for the thesis is detailed within the appendix section.

1.1 Research gap statement and open problems

This section highlights the open problems in existing studies and provided a research gap statement associated with the challenges that remain unresolved in the field.

1.1.1 Current open challenges

Although, several studies explored the role of DSM models on managing demand side electricity consumption, the major drawback is that there is limited or lack of research on how to position consumers as center of attention in DSM effort to collectively improve consumers' electricity consumption. Two key factors contributing to consumer reluctance in adopting new DSM technology/services can be associated with disengagement and the anticipated discomfort experienced by end-consumers normally associated with experiences such as level of invasion and consumer engagement [135]. These metrics often lacks clarity in definition in traditional models. Consequently, majority traditional DSM based DR schemes are considered invasive [37, 180] with limited attention paid to users' comfort and an alternative where ESCOs provides energy efficiency recommendation services are less-scalable [99] and error prone [137]. Note-worthily, emerging technologies such as industry 4.0 and the smart grids are changing this narratives. A key aspect of the smart grid vision is the deployment of smart meters, which will enable autonomous software agents to represent consumers and optimize their device usage. To date, smart meters have primarily been designed as information-providing devices, leaving it up to users to manage their home devices in the hope that they will reduce their energy consumption [157]. Additionally, smart grids aim to ease the integration of renewable energy and offer additional energy efficiency benefits. The problem of daily and seasonal variations, intermittent generation, along with limited predictability hampers the progress towards its effective deployment for DSM purposes. This is a development that calls for deployment of advanced predictive and analytics models. In a deregulated electricity market, entities (i.e. electricity consumers) have choices and enjoys equal access to the power plants and transmission lines as the utilities. It is necessary to equip consumers with critical and innovative technologies to help achieve their energy efficiency goals at scale. These solutions are used for service provision that allows forward-thinking, digitally compliant electricity utilities and consumers to assert their claim in the rapidly evolving digitally compliant ecosystem of electricity energy. This thesis therefore identified the following research gaps in existing DSM literature:

1. ESCO based energy efficiency services have been considered as suitable alternative to traditional invasive DR schemes. They are however less-scalable and error prone.

2. Current state-of-the-art models for estimation of consumer energy profiles have proven inadequate especially in situation where intermittent RES is integrated or the market experience shocks. This is a development that calls for deployment of innovative predictive and analytics models.

3. Electricity end-user engagement is another non trivial component for successful adoption of DSM schemes. How this metric is incorporated into traditional DSM is unclear and may therefore reacquires further attention.

4. Electricity end consumers comfort are crucial element in the successful adoption of DSM solutions but are often overlooked by traditional DSM. Demand response have potential to impact consumers comfort levels significantly. There is therefore a need for metrics that helps estimate whether a DSM effort is invasive and whether it is comfortable for consumers to carryout or not.

1.1.2 Research gap statement

In recent years, substantial progress has been achieved in the field of DSM. Nevertheless, the advances associated with current energy management framework largely isolates electricity consumers, limiting their active participation in energy optimization processes. This disconnect prevents consumers from effectively managing their energy usage and benefiting from potential cost savings and efficiency improvements offered by advanced energy management technologies. In same vein, inaccuracies in electricity asset modelling results in inability to fully account for the complexities and variabilities of real-world energy consumption patterns. Consequently, there remain several unresolved issues that require attention, particularly within the context of consumer comfort, engagement, electricity asset modelling fidelity and user behaviour extraction. Regarding the aforementioned points, this work focuses on addressing these major issues. This thesis recognizes the necessity for an advanced energy management system that optimizes energy usage while also taking into account customer behavior and comfort, a key elements frequently neglected in traditional demand-side management systems.

There is need to formalise an improved DSM framework that incorporate important metrics some of which include consumer engagement and comfort which closely relates to the level of invasiveness associated with traditional/state of the art DSM schemes. This thesis therefore aims to introduce the concept of IES incorporated based on novel predictive hybrid DT modelling of individual electricity asset for non-invasive actionable efficiency recommendation and new consumer evaluation metrics (i.e. CCI, and EI) towards improving the state-of-the art DSM scheme.

1.2 Research questions

There is a growing need to reconsider the idea of energy preservation and to implement essential measures. Innovative energy services (IES) can be useful in the field of demand-side management (DSM). Consequently, this thesis intends to find answers to the following main research question:

> *How can consumers be equipped with intelligent energy solutions/measures such as innovative policies or ES and what elements of IES should the implementation of proposed intelligent energy solutions comprise?*

The study's precise research questions are:

R1 How can digital twin model of an individual electricity asset be configured so that it is capable of coping with the challenges associated with real-world deployment for demand-side recommendation services?

R2 How can we elicit consumers' energy behaviour attributes for generating noninvasive and actionable recommendations for demand-side recommendation services using graph-based ranking model? And what is the optimal graph-based ranking model (e.g. PageRank) for scoring electricity asset/devices profiles?

R3 What impact does a conversational chatbot and extended reality (XR) as a DR strategy have on the adoption of IES, particularly on the mitigation of high levels of end-consumer disengagement?

R4 How efficient is the application of multi-agent reinforcement-learning-based control schemes and active BESSs for improving the end consumers' comfort level while using DR solutions?

To summarise, this paragraph helps to translate the individual research question into their associated problems. In addressing the research questions posed at the outset of this investigation, the subsequent sections of this paper systematically unpack the complexities surrounding our topic of interest. The background and challenges section (see Section 2) (literature review) delves into the existing body of knowledge, identifying gaps and underlining the relevance of our inquiries within the broader academic discourse. This section provides answers to research question R1. Following this, the methodology section (see Section 3) outlines the rigorous approaches undertaken to ensure the reliability and validity of our findings, directly correlating with the research questions R2 to R4 to affirm the study's foundation. Specifically, Section 3 provides answers to research questions R1. Section 4 provides answers to research question R2. Research question R3 is addressed in Section 5, while Section 7 addresses research question R4. The results are then presented, offering a direct response to our questions through data-driven insights. Finally, the discussion synthesizes these findings within the context of our initial inquiries, critically analyzing the implications and potential limitations and suggesting avenues for future directions. Through this structured exploration, the paper endeavors to contribute meaningful answers to the posed questions, advancing understanding in the field. Table 1 provides a summary of the research questions, together with some chapters/sections and the publications associated with each research question.

Table 1: Research questions.

Research question	Thesis section	Publication
R1	Section 2, Section 3	I, IV, II, VII
R2	Section 4	III
R3	Section 5	VIII, IX
R4	Section 7	V, VI

1.3 Statement of novelty

This thesis introduces a novel approach to energy management by integrating advanced methods for energy management efficiency services delivery, offering unprecedented techniques some of which include improved asset based behaviour prediction using hybrid DT and graph-based electricity asset behaviour scoring without the needs for additional model training. New metrics such as engagement index and comfort index for estimating user engagement and comfort respectively were introduced to validate the level of comfort and interactions of consumers with the proposed framework. This innovative method bridges the gap between theoretical models and practical applications, setting a new standard for smart grid technology. Details of individual elements comprising proposed novel framework are as follows.

Hybrid DT: Additionally, the proposed hybrid DT prediction models significantly enhance the accuracy and reliability of asset based energy predictors. The proposed hybrid approach utilizes domain-specific physical constraints and data-driven techniques, resulting in a narrower gap between simulation and reality and improved prediction accuracy. Industry 4.0 digital twins offer the chance to achieve a more profound level of analysis and intelligence gathering from data. This serves as a new method for standardizing Digital Twins (DTs) modeling of electricity assets, enabling secure and transparent communication between various electricity entities. This hybrid DT serves as a decision support system for participation in demand response (DR) electricity markets.

Graph-based behaviour scoring: A novel element introduced in this PhD research is the graph-based behaviour scoring framework, which facilitates the quick assessment of the end consumers energy behaviour for the identification of important behaviour patterns. This approach requires no need for training. Additionally, consumers are provided with noninvasive and actionable energy efficiency recommendations based on the scoring of their electricity profiles.

Conversational chat-bot and Engagement index: Furthermore, in order to improve electricity consumer comfort, the author of the PhD thesis proposed a novel metric for estimating consumer engagement termed engagement index. The innovation of this study comes from broadening the current scope of demand-side recommender systems by incorporating a conversational chatbot interface for Digital Twins of electricity grid assets. This enhancement actively engages and monitors end-user energy behaviors while providing tailored advice on energy efficiency, supporting the energy conservation goals of smart grid consumers.

Control and consumer comfort: The proposed MARLISA control scheme for controlling active BESS significantly enhance consumer comfort. This study's innovative aspect is emphasized through the use of distinct class of active energy storage systems controllers. These controllers regulate Battery Energy Storage Systems (BESS) technologies independently from loads affecting consumer comfort. They also facilitate energy efficiency optimization for individual microgrid assets or devices. This approach enables simulations at specific microgrid component levels, rather than focusing solely on optimizing general energy behavior for end-users, thus aiding in achieving their energy efficiency and comfort objectives.

In this context, the present research concentrates on advancing demand-side management using an innovative combination of technologies, including hybrid Digital Twins (DT), recommendation systems and multi-agent reinforcement learning (RL) models, to enhance end-user comfort and engagement in a distributed power grid.

The research related to the aforementioned questions in section 1.2 has led to the contributions summarized in the following section.

1.4 Contribution of the PhD thesis

The PhD thesis' unique contributions, as outlined in this doctoral dissertation and elaborated in the accompanying publications consist of the following:

- We conducted a trend analysis on the evolving role of Digital Twins (DT) for Demand Response (DR) applications, with the aim of establishing the potential of the proposed framework for the integration of DT and ecommerce recommendation services in future DR electricity markets. A comprehensive framework at the system level for Digital Twins based demand side recommendation services as a DSM scheme has been devised and put into operation.

- The integration of a hybrid Digital Twin model of individual end-user electricity assets, augmented with domain-specific physical constraints and laws, aims to enable detailed analytics and feedback at the atomic level. This novel setup also facilitates interaction at the individual asset level through the proposed conversational chatbot. The developed hybrid DT approach utilizes domain-specific physical constraints and data-driven techniques, resulting in a narrower gap between simulation and reality and improved prediction accuracy. The hybrid Digital Twin achieved a reduction of up to 84.132% in prediction error as measured by Mean square error (MSE) metrics.

- This thesis further contributes to the field of DSM by presenting a novel development of a graph-based ranking algorithm, for end-consumer electricity profiles scoring which enables provision of non-invasive and actionable efficiency recommendation at asset level. Additionally, a comparative analysis of state-of-the art ranking model was conducted revealed PageRank model as optimal choice for recommendation provision. The experimental results demonstrate a substantial enhancement in PageRank rating quality compared to the current state-of-the-art methods. PageRank returned about 78.9% capacity to accurately score consumption profiles, which is only closely followed by hyperlink-induced topic search (HITS) with 41% accuracy.

- The thesis introduces a proof of concept for a GPT-based conversational chatbot interface designed to enhance consumer engagement in demand-side recommender systems. The thesis adopted consumer engagement index (EI) metrics for evaluation of consumer engagement with demand side recommendation services. The findings indicated a 69% rise in user engagement with efficiency recommendation tips compared to the baseline scenario.

- This thesis showcases the utilization of multi-agent reinforcement learning models to improve end-user comfort. A distinct category of active energy storage systems controllers designed to manage BESS technologies by isolating them from the loads that affect consumer comfort. The thesis adopted consumer comfort index (CCI) metrics for evaluation of consumer comfort. The results of the study demonstrate a substantial 94% enhancement in comfort for certain loads.

1.5 Thesis structure

The thesis comprises seven chapters whose research topic can be broadly categorised into two subtopics, namely hybrid digital twin behaviour modelling and demand-side recommendation services. Following the introduction section, the thesis is logically divided into the following sections. Section 2 discusses the related works in the development of innovative energy services for behavioural reflective attributes and intelligent recommender systems. Section 3 is dedicated to the description of the methods associated with the development of scoring/ranking models. Section 4 describes the method relating to digital twin consumer recreation, recommendation provisions, and DSM solutions. The description of future work is contained in Section 5. A short description of each chapter is presented in the following:

- Chapter 1 is devoted to the introduction of the thesis. The introduction comprises the introductory content on innovative energy services for demand-side management and intelligent recommendation systems.
- Chapter 2 comprises the background and challenges of study required to understand the research questions and associated research problems of the study. In addition, it provides a comprehensive look at state-of-the-art works.
- Chapter 3 discusses various modelling technologies in relation to the proposed hybrid digital twin modelling approach.
- Chapter 4 explains the technologies associated with demand-side recommendation services.
- Chapter 5 discusses demand-side conversational chatbot, consumer engagement index (EI), and mixed reality application integration.
- Chapter 6 addresses multi agent reinforcement learning control (multi-agent reinforcement learning with iterative selective actions: MARLISA) and consumer comfort index (CCI) for improving end-consumers' comfort level.
- Chapter 7 covers the conclusion of the thesis and future plans.

2 Background and Challenges

This section explores the typical technologies utilized to attain the proposed solutions and emphasizes the key concepts. The section delves into IES by examining different elements of consumer-driven innovative models and their connections to energy efficiency services, particularly concerning behavioural changes on the consumer side.

2.1 Energy services (ES)

The notion of ES revolves around the efficient comprehension, prediction, and modelling of demand-side energy reduction and management [59]. Moving away from the core energy sales business [118], there has been a shift among energy service companies (ESCOs) towards servitization [155]. This transition has seen ESCOs offering a spectrum of 'efficiency services' such as advice, energy-saving implementations, and equipment installations through performance-based contracts [119]. While the term 'energy services' has triggered debates in scientific literature, Fell's work [51] in 2017 aimed to resolve the discrepancy. It revealed that variations in the term's interpretation could stem from diverse scientific fields and perspectives on energy utilization. Recent discussions on the concept of ES have been outlined in [51] and [82]. Fell's study [51] highlighted that ES represent functions reliant on energy for their operation, serving as pathways to attain specific states or desired end services.

2.2 Innovative energy services (IES)

Energy service providers are encountering fundamental changes on a global scale [91], [109]. The emergence of smart technological solutions allows electricity end-consumers to redefine their roles, thereby transforming them into active players in the energy market. These solutions are used for service provision that allows forward-thinking, digitally compliant electricity utilities and consumers to assert their claim in the rapidly evolving digitally compliant ecosystem of electricity energy. Energy services' prospects look optimistic despite the fact that significant number of consumers are disengaged, uninterested, or unaware of the benefits offered to them. The reason for such disengagement in most cases is due to the lack of information or the fear of complications resulting from making changes. The success of innovative energy services can be fundamentally based on digitization, which introduces new opportunities that empower end-consumers. An example of such energy services includes notifications using abundant and reliable efficiency advice [109]. Figure 1 illustrates the rate of adoption of innovative services among member states of the European Union [14].

In this thesis, the notion of IES was synthesized from recent literature, focusing on a consumer-oriented framework. This model leverages intelligent components to non-intrusively offer recommendations aimed at influencing consumer behaviour towards embracing energy-saving choices across various categories such as Social (Soc), Economic (Eco), and Technical (Tech) choices [149]. For a comprehensive assessment of energy wastage, we delved into the identified IES model employing two significant tools or contributing technologies: the recreation of energy consumer digital twins, and a recommendation system providing actionable insights.

Technological innovations: The innovation ecosystem delineates the setting in which interactions involving the exchange of technology and knowledge take place [90]. Digital technologies have proven to be a powerful catalyst for innovation across different economic domains. Digitization in the energy sphere has notably contributed to stabilizing the electricity transmission grid by bolstering reserves amid variable energy sources such as solar and wind. The integration of individual objects through the internet of things (IoT) creates an extensive avenue, enabling electrical devices to play a role in expanding the ecosystem for distributed energy resources. Consequently, digital advancements in the energy sector, facilitated by the advent of IoT, have offered a convenient means of incorporating non-human elements into the management strategies of digital innovation and its associated ecosystem [88]. In prior studies, work [20] has explored the technological innovation system and its interactions within broader contextual structures. Yang et al. [198] presented an analysis of energy technological innovation, comparing renewable energy and fossil energy perspectives. Their findings indicated that the impact of technological innovation on fossil energy surpasses the impact on renewable energy in terms of pricing. This led to a reduction in renewable energy prices to below the optimal rate, emphasizing the need for a pricing mechanism to support the advancement of renewable energy technology in China. The study also highlighted the crucial role of government policy support in facilitating the development of these proposed innovative technologies. Recent academic literature has notably emphasized the system concept approach in policy-making and innovation systems [166]. The energy sector's innovation necessitates a well-defined set of metrics for assessing energy performance concerning the innovation system [116, 28]. A study by Miremadi et al. [116] identified approximately 120 indicators, classified into categories such as policy, impact, input, output, structural, and systematic indicators. These were linked to four criteria—availability, understanding, relevance, and measurability—highlighting significant weaknesses in the existing indicators. Additionally, in the technological sphere, 90 indicators were utilized to align with seven functions of technological innovations within the system, presenting potential avenues for crafting policy recommendations. While traditional methods relying on expert advice have proven effective, they often struggle to scale up to address a large number of consumers [173]. Studies focusing on persuasive technology suggest that innovative technical solutions could be the key to assisting consumers in achieving their energy efficiency objectives.

Economic innovations: Efficient energy use drives economic growth. To meet the demands for such development, enhancing energy consumption through structural advancements and innovation funding is crucial for greater economic advantages [55, 79, 108]. Politically, the government can establish a funding framework for low-carbon innovations within the context of a low-carbon economy. This framework integrates environmental and innovation policies, expanding on various perspectives [191]. The successful integration of corporate practices and the adoption of eco-innovations to combat climate change rely on the resources and support available to organizations [156]. The authors in [30] highlighted that the energy system and spatial differences have significant implications for economic growth and development. Innovations within the energy sector often emerge from geographically defined clusters [17, 40], which serve as global hubs for low-carbon energy innovations and play a pivotal role in regional economic prosperity. Jabbour et al. [79] explored the application of eco-innovation in creating sustainable supply chains for a low-carbon economy. Similarly, [108] outlined an optimized economic model that relies on clean and renewable energy, particularly geothermal energy, as a critical factor in fostering sustainable economic development.

Social innovations: Social innovation will play a critical role in transitioning towards low-carbon energy systems [71, 165, 193]. This involves initiatives aimed at achieving social objectives, enhancing community well-being, and empowering civic engagement. Often, research has focused separately on the technical and social aspects of energy systems, yet the latter is integral for the acceptance and adoption of such innovations by society. Work [1] introduced an innovation model centred around city neighbourhoods and social networks to promote the adoption of renewable energy technologies (RET). They developed Twitter-based constraints derived from the geographic context of Qatar. Subsequently, the diffusion rate of RET innovation was assessed using a combination of Twitter networks and household diffusion patterns, employing an adapted linear threshold technique to disseminate information. [71] conducted a survey on community energy solutions driven by citizens, establishing operational criteria under the concept of social innovation. Work [90] addressed the role of residential prosumers in introducing innovation into the energy ecosystem, aiming to ensure flexibility in future energy systems. Their proposed approach—blending social-technical aspects and diffusion strategies—targets government initiatives to combat climate change and advances in ICT and consumer electronics. Lastly, authors in [193] explored the application of social innovation within socio-technical energy systems.

Innovation diffusion: Diffusion represents the spread of an innovative idea within a social system by its members through specific communication channels [161]. Successful implementation of these innovative solutions relies on achieving high consumer adoption rates, indicating the number of individuals in a society who start using a new technology or innovation within a given time frame. This emphasizes the pivotal role consumers play in the process of adopting innovations [91]. For successful diffusion, a typical process involves several sequential stages: (1) acquiring knowledge about the innovation; (2) developing an opinion or attitude towards it; (3) making a decision to accept or reject the innovation; (4) executing the decision (e.g. enrolling in a green tariff, becoming a prosumer, utilizing a social media platform); and (5) validating the decision, indicating satisfaction that leads to continued usage or dissatisfaction that results in discontinuation of adoption [91] [161].

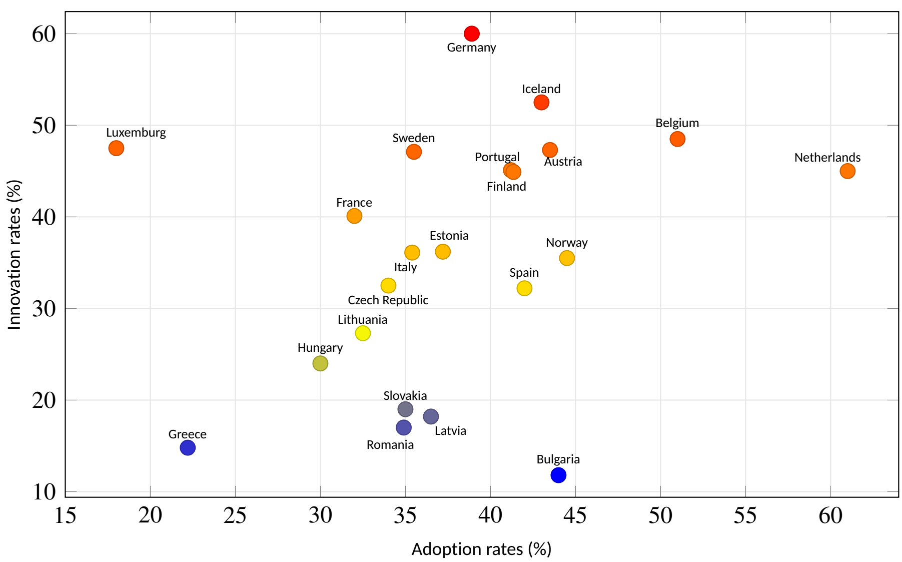


Figure 1: Innovative services adoption rates [142].

2.3 Industry 4.0

The initial industrial revolution transformed manufacturing by substituting human and animal energy sources with water and steam engines. The subsequent industrial revolution, often termed the technological revolution, facilitated economic progress and efficacy by introducing machines and electricity into factories, establishing telephonic networks, and constructing extensive railways for both transportation and information exchange. Following this, the third revolution, known as the digital revolution, ushered in the widespread use of computers and communication technology within the production sphere [167]. The concept of 'Industry 4.0' emerged in 2011, rooted in advancements in robotization and the automation of manufacturing processes, which were regarded as pivotal components of the third industrial revolution. The fourth industrial revolution encompasses various modern technologies, including the internet of things (IoT), artificial intelligence (AI), advanced simulation, big data analytics, and the integration of intelligent devices and products [48, 70].

Industry 4.0 digital twins: Among the rapidly evolving concepts within Industry 4.0, digital twins have garnered attention. Grieves initially defined digital twins as physical entities paired with their corresponding virtual representations in a digital space, interconnected via data links [27] (details in Figures 2 and 10). Lately, digitization has significantly impacted the way people live, fostering greater connections between products and their surroundings. A digital twin (DT) provides a comprehensive digital portrayal of the various conditions and characteristics linked to consumers. Its purpose is to analyse real-world behaviour by leveraging data and models. Employing the concept of a digital twin allows us to model energy consumers, with an aim to rectify behavioural gaps and enhance energy efficiency [69]. The design and application of digital twin technology in the energy sector necessitates a shift in perspective—from an industry or utility expert-focused approach to a new user-centric or consumer-oriented methodology. The suggested framework, centred on consumers, originates in a modelling method that combines various elements, such as recommender systems (scoring or ranking algorithms), analysis of historical and social media metadata, short and long-term energy predictions, machine learning models, and visualization. This integration aims to digitally replicate consumers' energy profiles based on their behavioural patterns.

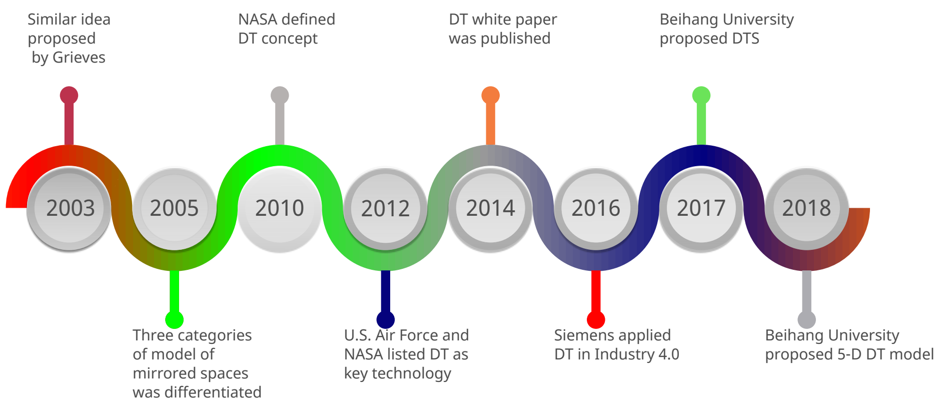


Figure 2: Digital twin development milestones.

(a) Data and metadata analysis (feature extraction): Raw data cannot be directly ap-

plied to forecasting or recommendation systems. Hence, it's crucial to identify the primary variables impacting energy forecasts. Consequently, considerable effort is directed towards preprocessing the data to extract essential features such as temperature, time, geographical location, social behaviour, and more.

(b) Energy forecasting: Forecasting loads stands as a pivotal element within a household's energy management system, encompassing short, medium, or long-term predictions. Accurate predictions play a crucial role in comprehending consumer behaviours and patterns. Given its significance within the energy culture, load forecasting receives special attention, complemented by other features derived from the analysis of metadata. Predicting energy consumption is influenced by multiple factors, including seasonal variations, weather conditions such as wind speed and precipitation, day-to-day fluctuations, customer demographics, and time of day. Typically, load forecasts targeted at residential consumers can be based on short-term predictions (around one day ahead) due to the challenges associated with accumulating errors over longer periods. Consequently, these complexities have spurred the development of various techniques for price and electricity forecasting [169].

2.3.1 Demand side management (DSM) in Industry 4.0

DSM techniques encompass two primary categories: demand-response (DR) and energy efficiency (EE) schemes (refer to Figure 3). DR is further divided into incentive-based, known as direct load control [26], and pricing-based, referred to as indirect load control [105]. Figure 3 illustrates the various DSM schemes encompassing DR and EE programs. In the incentive-based approach, energy utilities directly manage end-user electricity resources, which include household appliances and emerging electric vehicle (EV) loads, leveraging tangible incentives. Conversely, the pricing-based approach enables consumers to modify their consumption patterns in response to fluctuations in energy prices. In this framework, utilities establish energy price signals to encourage electricity consumers to actively switch their appliance usage to off-peak periods or when energy prices are lower. These modifications in end-consumers' energy/load behaviour represent the primary function of DSM. Recently, utility services have transitioned to e-commerce due to significant advancements in the Industry 4.0 domain. Digital twins (DT) augment the digital transformation of DSM schemes by providing new capabilities in decision support systems (DSS) [179]. This enhancement is observed in demand-side recommender systems [136] that target end-users by offering feedback on EE behaviour and educational programs.

Decision support system (DSS): Demand-side recommender systems have been utilized to enhance consumers' ability to navigate information overload and product abundance issues. These systems generally fall into three categories: content-based, collaborative filtering, and hybrid approaches. The content-based method suggests items akin to those previously favoured by individual users. In contrast, the collaborative approach operates under the assumption that users who share similar preferences tend to rate items similarly. The hybrid approach combines elements from both collaborative and content-based methodologies [136].

Research into persuasive technologies revealed that consumers' pursuits for self improvement can be achieved using technological intervention. In the field of energy, tools such as social comparison, feedback, and goal setting have effectively influenced consumers' tendencies to be conservative in their behaviour. From a traditional perspective, the advice-based approach is another effective technique. Yet, it is challenging to expand this to accommodate a larger user base. Recommender systems offer a better solution

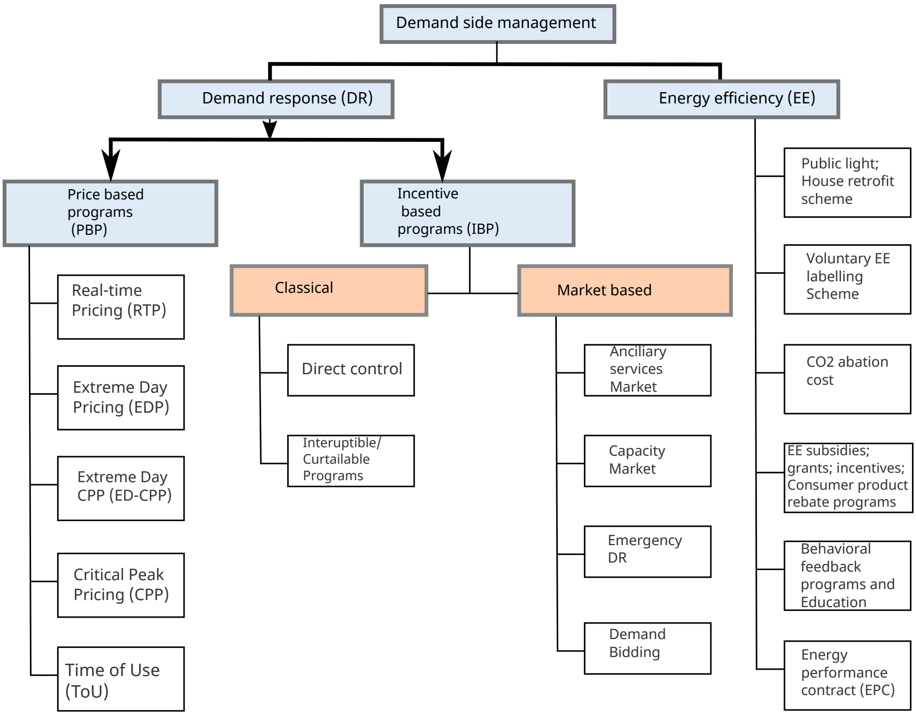


Figure 3: Schematics of DSM main and lateral categories [144].

that effectively scales energy-saving potential for a wider audience [173]. Studies on persuasive technology indicate that the use of technological solutions can assist consumers in their quest for self-enhancement. These systems aid consumers in maximizing their choices and opportunities for saving energy. As a result, integrating recommender systems into energy services could significantly amplify their impact on consumer energy habits. To tackle this issue more effectively, we introduce a tailored framework designed to accommodate diverse consumption categories and their unique attributes. This framework comprises three primary facets for delivering recommendations: business and industrial, residential, and policy-related.

(a) Business and industrial: Characteristics within this group utilize specific data linked to businesses, encompassing the types of machinery, equipment, and devices utilized in production processes. Typically, user actions and energy usage profiles are analysed by the framework to determine similarity in recommendations. These recommendations are formulated based on data collected, which could include heat-related information and data from electric drives.

(b) Residential: Energy stands as a fundamental element in contemporary living, essential for both household and business operations. Household energy consumption accounts for approximately 27% of the total energy usage in the entire EU. Key determinants influencing household energy consumption encompass income levels, household size, geographical location, traditions, and cultural backgrounds. These factors can be manipulated to create digital representations of residents, aiding in more effective management of their energy consumption.

(c) Policy: The adoption of innovative energy services hinges on various factors, including behavioural shifts and the acceptance of new technologies. Successful policy implementations could lead to institutionalizing effective energy management strategies. Citizens play a primary role in embracing and ensuring the success of these innovative solutions.Consumers across the EU will be offered access to reliable tools for comparing energy prices in the future. Moreover, an improved regulatory framework creates opportunities for civil society involvement in responding to price signals and shaping the entire energy system. The evolving behaviour of energy consumers remains a significant focal point for energy policy-makers. With residential consumers accounting for about one-third of global energy consumption, governments worldwide are actively seeking smart and innovative approaches to promote energy-saving prospects. Regulating energy consumption in residential spaces without causing disruptions among residents poses a considerable challenge. Consequently, reforms aimed at identifying the energy system's needs and providing adequate incentives to support such initiatives are necessary.

Consumer behaviour analysis: Comprehending the daily routines that shape consumers' energy consumption behaviour is pivotal for successful DSM initiatives. Moreover, raising awareness and providing education are as significant as financial incentives in advocating for DSM solutions [124]. Consequently, consumer scoring aids in steering behavioural adjustments towards achieving a transition to reduced energy consumption. We tackle this issue by characterizing consumer behaviour through graph-based analysis. The energy profile of consumers can be depicted as dynamic information flow over time, which significantly shapes the evolution of the topology within the behaviour graph, involving the emergence and decline of edges and nodes. One extensively studied issue concerning network evolution is link prediction, forecasting potential future links. Ranking involves analyzing and predicting load dwell times, which can then notify consumers upon identifying a common load level (base, medium, or peak). Graph-based ranking models can predict consumer or node transition behaviours in this context.

Behaviour ranking and recommendation services: Determining the influence of occupants on building energy usage has gained significance lately. This is because various factors such as urban climate, building traits, occupant actions, and building operations are interconnected, making it difficult to isolate the occupants' specific role in energy consumption. One potential resolution involves implementing innovative, consumer-centric approaches to compare energy profiles among consumers, revealing ranks, and offering actionable suggestions to enhance their ranks, thereby influencing reduced consumption [11]. The suggested approach consists of two tiers. The initial stage involves assessing the energy consumption attributable to occupants, eliminating factors not associated with occupant behaviour. The subsequent phase involves ranking buildings based on the achieved and potential energy savings within the analysed time frame in order to provide demand-side recommendation service. Figure 4 depicts details of recommendation system for energy applications. Specific areas of application can be further categorised as follows:

- Application to DSM
- Application to intelligent services and e-commerce
- Application to consumer behaviour
- Industrial and business, residential, and policy-based
- Social, technical, and economic

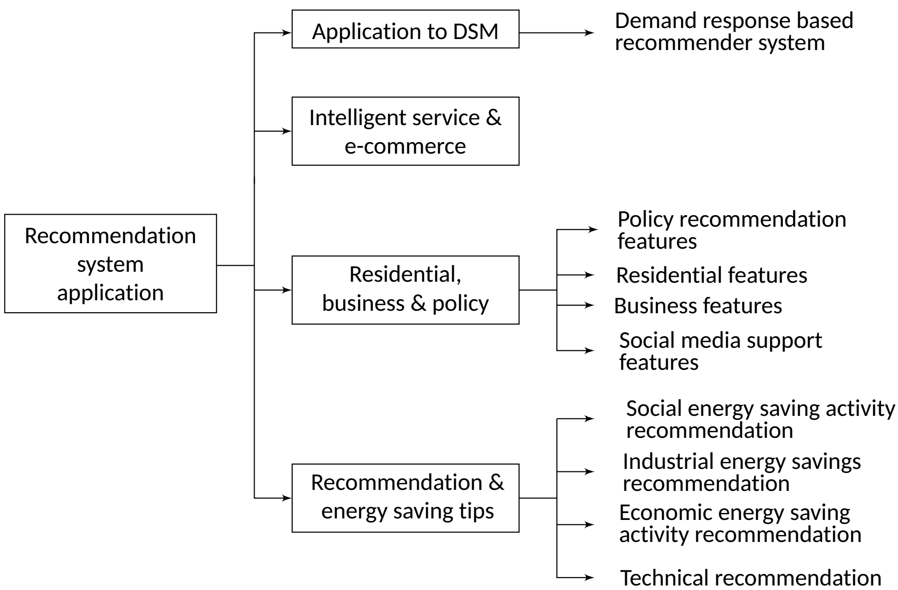


Figure 4: Recommendation system application [142].

2.4 Beyond-energy services

It is widely acknowledged that what are referred to as 'energy' services rely not only on energy-using devices but also on various other products, infrastructures, and resources such as labour or end-consumer experience [118]. However, the implications of end-user comfort while using a DR solution and engagement with DR schemes are equally worthy of examination. The notion of meta-services can offer additional insights, particularly when considering end-users' comfort and engagement as an example.

2.5 Challenges of proposed IES model

Despite the substantial benefits linked to IES, there are instances where consumers face barriers or encounter challenges in effectively adopting these services. These hurdles might stem from financial constraints or insufficient governmental support allocated for the uptake of IES. Additionally, limitations may arise due to the absence of energy audit reports and the necessary recommendations to enhance energy efficiency through the adoption of IES. Once energy audit recommendations are acquired, they might be perceived as symbolic gestures and not effectively put into practice. At times, local authorities establish ambitious targets that may not be practically achievable but are primarily driven by political motives to meet climate objectives or gain international recognition. Furthermore, local authorities can lose sight of their role in initiating and supporting the implementation of IES, leading to a loss of focus and detachment from achieving successful IES implementation goals. In various instances, standstills arise due to unsatisfactory experiences with prior or similar IES projects, significantly influencing the adoption of new or akin services by consumers. Behavioural barriers [91] have been proposed as contributing factors, stemming from bounded rationality. These include limitations in information, constraints in information processing capacities, inertia, or risk aversion, impeding consumers from making fully rational choices towards adopting IES as the optimal solution. In numerous cases, stagnation emerges due to dissatisfactory encounters with previous or similar IES initiatives, exerting a significant influence on consumers' willingness to adopt new or similar services. Identified as behavioural barriers [91], these factors are rooted in bounded rationality, encompassing limitations in information, constraints in information processing abilities, inertia, or risk aversion. These constraints hinder consumers from making wholly rational decisions regarding the adoption of IES as the ideal solution.

2.6 State of the art in innovative energy service-based demand-side recommendation services

This section examines the state-of-the-art works and opens substantive discussion on the concept of innovative energy services (ES). It further highlights the gaps and limitations in the current literature that pertain to the research questions outlined in section 1.2.

Energy services: From a literature perspective, the authors in [51] conducted a content analysis and literature review aimed at providing an answer to the question: What are energy services? They noted that significant initial investigations did not clearly uncover the prevailing definitions of the term 'energy services' or consistent examples to illustrate it. Frequently, it is mentioned that individuals are not seeking energy in itself but rather the functional benefits or 'energy services' it delivers [51]. Energy services encompass the various processes and forms of energy that end-users ultimately benefit from and utilize to extract value from energy carriers, such as electricity and gas [67]. The topic of 'energy services' was discussed e.g. in work [171]. The study noted that the term 'primary energy' refers to the energy contained within natural resources such as coal, crude oil, natural gas, uranium, and even sources like falling water. These resources can be extracted, stored, utilized, or collected but have not yet undergone conversion into different energy forms. 'End-use energy' signifies the energy contained within primary energy that is delivered to consumers at the end-point of use, such as kerosene, gasoline, or electricity distributed to residences and industries. This ’end-use energy’ is then converted into ’useful energy’, ’useful energy demands’, and ’energy services’, such as heat for cooking or air circulation obtained from mechanical energy. The author in [85] noted that the use of energy involves transforming it from one form to another, which consistently incurs a certain expense. The expense of useful energy can significantly vary from that of the initial energy source or fuel. Consequently, experts in the energy field are increasingly emphasizing the delivery of energy services rather than solely focusing on energy supply. Work [67] presented a study on the application of the energy services concept to energy systems sustainability. Work [54] noted that the price of energy over the past five hundred years was not upward trending; this means that the economy might not be faced with scarcity. On the other hand, the author draws attention to technological improvements that are capable of inducing increased prices in contemporary times not because of scarcity but because of greater added value. This is because consumers are likely to pay more if they are able to get more value from the introduction of new/improved fuel or technology. Previous ideas on ES from the literature were presented by [51, 82]. In [51], the authors reported that ES encompass activities dependent on energy for their execution, serving as a means to achieve specific desired states or final services. Morley’s work [118] in 2018 offered a review emphasizing the socio-cultural and dynamic aspects of ES, labelled as meta-services. These are shaped not only by energy supply, governance, or consumption but also by other non-energy-providing organizations, aiming to effectively stabilize the demand for ES.

The earliest works on ES and energy service companies are described in work [95], which noted that the idea of energy performance contracting (EPC) termed Compagnie générale de chauffe (CGC) originated in France about a 100 years ago. The author in [148] noted that ESCOs operated on a considerable scale since the late 1980s to the early 1990s. The original concept of the European ESCO originated in Europe over a century ago and later spread to North America [22]. The author in [148] explained that ESCOs and EPCs are tools used in the promotion of energy efficiency and integration of RES. The primary role of ESCO was to help consumers identify the hurdles hindering energy efficiency and to delineate key theoretical obstacles affecting energy efficiency. These include imperfect information, principal-agent relationships, split incentives, concealed expenses, limited access to capital, and risks. [177]. ESCOs and EPCs are prevalent strategies aimed at bolstering sustainable energy usage by encouraging energy efficiency and renewable energy sources. They serve to address financial limitations in investments and offset initial expenses by utilizing the energy cost savings derived from reduced energy demand. ESCOs offer the chance to mitigate rising energy demands and regulate CO2 emissions. They leverage market advantages by reducing energy expenses for their clients, concurrently generating profits. Work [63] noted that ESCOs emerged within regulated markets to offer services that extended beyond those offered by regulated providers. This includes services such as maintenance of appliances, selling of appliances, and performance of energy audits/demand-side management. Another important function of ESCOs includes DSM bidding, where electricity utility companies request/appeal for the interest of ESCOs to help them achieve the designated quantities of DSM savings (i.e. 1000 kW reduction in demand) [184].

ESCOs operations are for profit and have maintained their conventional functions in a restructured market while also adopting new roles aligned with the restructured market’s dynamics [63]. Study [110] noted that the shift in the current electric power sector towards sustainable energy production relying on renewables will alter the industry’s framework. As a result, utilities, being the primary stakeholders in this evolution, will encounter fresh hurdles in their business practices. To stay competitive in the evolving energy environment, they will need to modify their business frameworks. The authors further presented a review of two unique business model comprising of utility-side business models and customer-side business models while noting that the two basic choices follow the alternative logic of value creation. The article indicates that established plans for business models on the utility side exist, while business models targeting customers are still in an early phase of advancement. In contrast to the utilities approach to ESCOs for the DSM functions described in [184, 63]; In [107], the author noted that threat of tightening profit margins and rising competition is compelling the energy industry (i.e. German utility companies as a case study) to look for methods to prevent a commodity trap through the provision of distributed energy systems. Similarly, changing consumer preferences, regulatory frameworks, and digitalization are creating avenues to enter the unprofitable segments of customer markets. Several market players, such as established utilities, battery providers, or independent start-ups, present competing business models that cater to distinct customer environments, each offering specific advantages [107]. In a similar study presented by [84], the author identified the need for the provision of modern energy services for the rapidly growing energy consumption among low-income urban dwellers, which constitute over 50% of total households in sub-Saharan African countries. Work [29] investigated the relationship between energy services and environmental degradation and energy poverty. They discussed the need for the provision of universal access to modern energy services in resolving environmental degradation and poverty-related problems. Work [107] noted that distributed energy promotes the development and relaunch of new products. Packaged components such as renewable production, storage devices, and heat pumps are increasingly integrated into ES. The offerings are tailored either for existing installations or target consumers with older or non existing installations. These offerings encompass storage solutions, energy management tools, or smart home devices. Some of the emerging business models also encompass involvement in a virtual power plant. This setup aggregates and optimizes both customer load and producer supply, enabling the excess energy to be offered in wholesale markets for revenue generation. Enhancing energy efficiency is limited by physical constraints within energy technology; it cannot be endlessly improved. Nevertheless, fundamental technological advancements can result in significant leaps in efficiency, such as transitioning from working animals to vehicles or from internal combustion engines to fuel cells [67].

ESCOs limitations: While the ESCO business model as a traditional DR approach has suffered a number of setbacks/limitations in recent times, works from the literature further revealed that recent attempts by energy service contractors aiming to provide consumers with energy saving awareness are less scalable [173] and the results are error prone [120, 143, 138], especially when considered from the end-user perspective. Some other notable challenges from the state-of-the-art literature include liberalization policies, the difficulties associated with incorporating decentralized generation resources, and the latest flattening of demand for electricity caused by both economic downturns/market shocks (i.e. the COVID-19 pandemic) and technological advancements, which have resulted in reduced profits for European electricity providers. Notably, the author in paper [153] mentioned that while ESCOs represent a potentially highly promising business model that can aid in the transition towards a more sustainable energy system and help combat climate change, innovative and sustainable business models are necessary to cater to electricity consumers while considering the operational requirements of the system and ensuring the financial sustainability of suppliers [60].

In line with the arguments presented by [107, 110], study [32] describes innovative energy efficiency policies based on a state-of-the-art review. The author concluded that there is need to periodically update policies and track advances in technology. They further emphasised the need for policy-makers to develop a robust compliance regime owing to penitential tendencies for losing confidence in the reliability of EE programs due to noncompliance-related issues. The work of [60] noted that the need for an innovative and sustainable electricity supply business model can be attributable to a number of factors, including the flattening demand for electricity owing to the recent economic crisis, market liberalisation, the emergence of prosumers, and excessive generation. These factors resulted in volatility and a reduction in the amount of returns accrued by electricity utilities. Recent studies indicate that successful Industry 4.0 electricity consumers should combine their understanding with digital twin replicas of their microgrid assets, incorporating essential analytics skills [44]. An integral aspect of the smart grid is its ability to enable consumer involvement in overseeing the grid's overall management [18]. In Industry 4.0, the goal is to establish concepts of vertical and horizontal lifecycle integration, in which DT technology plays a pivotal role [8, 106]. Study [65] presents a general modelling framework for energy services supply. The proposed model uses data-flow networks for the representation of municipal or regional energy systems. More broadly, a business model outlines how an entity generates, delivers, and gains value, steering the execution of its strategy [146]. Examining business models in electricity provision is pivotal in steering the shift towards a more sustainable and decentralized energy sector. These models encapsulate the interactions among suppliers, customers, and operators [146].

Critical failures of traditional models: Current shifts in digitization and consumer expectations for personalized, top-tier products and services have highlighted the necessity to reassess digital twin concepts. This reassessment involves integrating recent enabling technologies, such as physics-informed machine learning [158]. This type of high-quality DT modelling approach is important to combat the limitations in traditional models in their ability to cope with unforeseen circumstances, such as market shock (i.e. the COVID-19 pandemic) and RES variability, which arises due to changing weather patterns. Grassroots research methodology has been employed to analyse the pandemic's impact on power systems across various nations, including the United States [3], China [126], Italy [61], Spain [163], Brazil [42], Canada [2], India [10], Sweden [83], Israel, Estonia, and Finland [35]. A notable trend observed in these studies is the pandemic's influence on energy consumption behaviour and peak demand. Primarily stemming from government-implemented preventive measures [25], numerous countries experienced a substantial decline in electricity usage in the commercial and industrial sectors [21]. This reduction posed several hurdles for electric utilities and system operators [202]. Challenges arose due to irregular consumption patterns, such as elevated voltage levels and imprecise load forecasts. Additionally, there were indirect consequences, including increased shares of renewable energy generation, resulting in challenges such as steep ramp rates and frequency fluctuations. Industry 4.0 enables more sophisticated analytics and the creation of avenues for end-consumers and decentralized grid assets (i.e. RES) to be modelled similarly to their DT counterparts. This development opens pathways for improved asset-level analytics.

Hybrid digital twin modelling techniques gain advantages through combining data-driven and physics-based models [96]. The accuracy of a DT model is contingent upon the model's intricacy [178]. In [100], the authors introduced a hybrid digital twin strategy tailored for zero-energy buildings (ZEB), integrating physics-driven and machine-learning techniques. Similarly, [53] demonstrated the use of a combined physics and data-driven DT model to enhance lithium-ion battery safety. The proposed model offers data-based forecasts while also delineating the comprehension of physics governing behaviour, especially concerning potential catastrophic failures. In the same vain, decision support systems can utilize digital twin predictions to involve users in demand-side management (DSM) activities. In a study presented in [77], a method employing human-computer interactions to enhance energy consumption, specifically emphasizing energy efficiency, was used. A similar idea was explored in [173]. The author argued that the advice-based approach such as recommender systems offer a better solution that effectively scales energy-saving potential for a wider audience compared to traditional approach.

Recommendation services: To achieve optimal energy efficiency, innovative strategies aimed at modifying energy consumers' behaviour will be crucial. Alongside various methods to prompt changes in consumer behaviour through attention triggers, personalized recommendations play a vital role in fostering sustainable advancements in energy efficiency. Addressing this challenge, the current study concentrates on innovative energy services leveraging intelligent recommendation systems and digital twins. We explore various trends linked to the development and adoption of energy services, considering the positive connections between recommendation systems and consumer energy behaviour on the demand side. The authors in [151] presented an enhanced decision-support tool based on a particle swarm optimization (PSO) algorithm for the optimization of residential consumers' acquisition of electrical energy services. The proposed DSS tool helps consumers to schedule available distributed energy resources (DER) to maximize net benefits. From the industry perspective, several hardware and software platforms have been proposed to give end-users the opportunity to monitor and manage their energy consumption. In the energy industry, the concept of recommender systems has gained significance. For the future energy system to prosper, the role of consumer choice and involvement has been highlighted as crucial. Encouraging sustainable shifts in behaviour, advocating for low-carbon technology, and convincing consumers to conserve energy are essential goals achieved through recommendations. These concepts have recently been addressed in projects such as PEAKapp [47], IntelliSOURCE [78], and Endesa [46], which aim to empower end-users in managing their energy. However, the majority of these solutions primarily target utility administrators.

The knowledge-action gap: Despite understanding the associated benefits of IES such as demand-side recommendation services and consumers' willingness to embrace them, this knowledge does not automatically result in the intended behaviour, leading to an intention-behaviour gap [91]. A literature review presented by [91] discussed incentives and obstacles related to the adoption of IES based on consumers' environmental behaviour. This review highlighted the intention-behaviour gap as a significant challenge in adopting such systems. Instead of concentrating solely on technologies and resources to provide units of energy such as kilowatt-hours or liters of fuel, nations are starting to recognize that the primary policy objective is to furnish the necessary energy services for sustainable development such as comfort, convenience, etc. [32]. Research shows that building a positive rapport and collaborative relationship between students and instructors in an interactive environment is highly important. Engaging students boosts their satisfaction, enhances their motivation to learn, reduces feelings of isolation, and improves their performance in online courses [111]. Study [160] proposes the use of contemporary but well-established technologies such as chat sessions to boost student engagement by incorporating technology into the learning process.

End-user comfort: Moreover, in a quick review of the literature, work [85] uncovers inconsistencies in examples of what constitutes energy services, and what potentially complicates the conceptual understanding. For example, work [51, 75] attempted to clarify whether thermal comfort can be classified as energy services. In the same vein, work [67] reported that energy is a crucial input for the production of all goods and services, being integral to both. However, people do not require or purchase commercial energy directly; instead, they seek the energy services delivered by the energy system, which transforms natural energy sources and flows into these services such as comfortable office rooms or warm dishes. According to an analysis presented by [67], one major conclusion is that there is a need for a thorough reevaluation to determine the per capita level of energy services that enhances human welfare and quality of life.

It is notable that there is limited evidence in publications linking energy consumers, DT, recommendation systems and energy conservation. Given the aforementioned limitations and gaps in the state-of-the-art research, this thesis centres on IES reliant on intelligent recommendation systems and digital twins. In contrast to prevalent utility-centred approaches, the thesis advocate a paradigm shift, placing consumers and individual electricity assets/devices at the forefront by employing their digital twins instead of the traditional client-focused strategies. The proposed concept aims to offer energy-saving alternatives without necessitating substantial changes to consumers' lifestyles. This could be accomplished by predicting consumer consumption patterns at the individual electricity device level while concurrently providing the necessary recommendations to optimize energy usage.

2.7 Research methodology

This section outlines the approach adopted by the thesis in order to provide relevant answers to the research questions (see details in Figures 5 and 6). The thesis employs the principles of innovative energy services (IES) to ensure that the designed and developed artifact addresses various issues related to associated with the implementation of consumer-focused and non-invasive demand side electricity management. The research methodology has been characterized in two distinct ways, primarily involving the literature review approach and the research design.

First, a state-of-the art analysis was conducted to formalise the concept of IES based on consumer-centric approach to demand side electricity management. Furthermore, a an ensemble of new technologies comprising of hybrid digital twin model was designed and demand-side recommendations was developed based on the electrical components of smart grid end-users to replicate the component specifications of a reference smart grid system. This approach aim to reduce net energy consumption at individual asset level. Additionally, the use of AI will link smart meters, IoT devices, and smart grid assets to the DT recreation of demand-side end-users, providing energy efficiency recommendations to enhance energy management and efficiency. Lastly, system has been assessed based on key metrics such as consumer comfort and engagement index in order to validate the proposed consumer-centric demand side recommendation framework. The system's evaluation is detailed in publications [IV, V, VI, VII, VIII].

2.7.1 Literature review methodology

The literature review is accomplished through a content analysis of the latest research, with a specific focus on the IEEE Xplore and Scopus databases. Using this analysis, we introduce fresh empirical evidence that supports the utilization of data-driven twin technologies as innovative methods for implementing consumer-centric demand-side management. These technologies involve sophisticated representations of consumer energy behaviours. Additionally, we have identified several hurdles linked to the adoption of energy services, particularly concerning the implementation and widespread acceptance of the digital twin concept. Energy services are grouped according to their similarities or

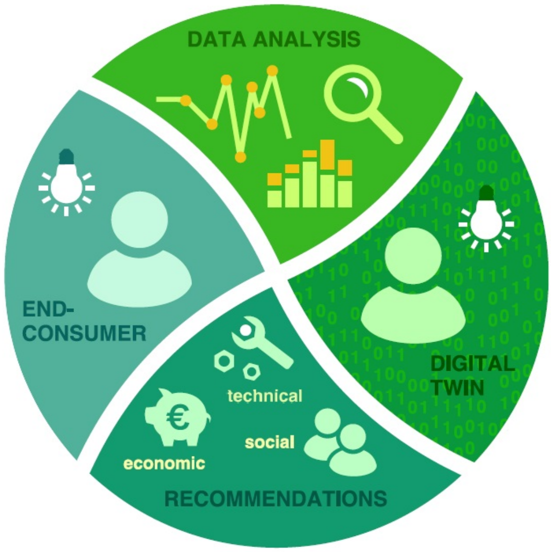


Figure 5: Overall scheme of the presented consumer-oriented framework for demand-side recommendation based innovative energy services. Approach includes four main elements: end-consumer, (meta)data analysis, digital twinning, targeted recommendations [142].

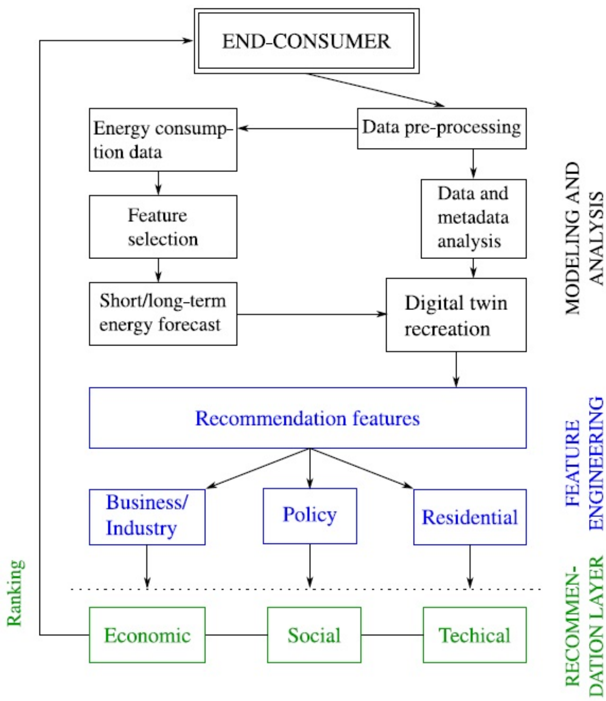


Figure 6: Detailed scheme of the proposed framework with different layers.

proximity, though some services may straddle multiple categories, leading to potential ambiguity in classification. Services related to water heating, space heating, cooling, lighting, and cooking are frequently identified as energy services. To retrieve the frequency of occurrences of specific terms, a set of key search words (listed in Table 2) was utilized as query terms in the selected databases.

Figure 7 visually represents the findings of an objective evaluation of IES literature derived from searches in the IEEE Xplore and Scopus databases. It illustrates the frequency of IES occurrences in publications from 2010 to 2019. Notably, from approximately 2013 to 2019, there was a noticeable upward trend in IES publications across both databases, signaling an approximately 83% increase in its adoption. This trend aligns with the typical S-curve pattern observed in the adoption of innovative services. Furthermore, a peak in the adoption of these services in 2012 was observed consistently in both databases. This rising trend can be attributed to various factors, often rooted in social or economic circumstances. It is plausible that the adoption of innovations served as a recovery mechanism following the 2008 global financial crisis. These innovations encompass enhancements in integrating and boosting the performance of renewable energy sources (such as PV photovoltaic systems), the integration of intelligent electrical network management, and the increase in private sector spending on energy-related research and development (R&D). There are notable signs indicating shifts in the private energy sector's R&D spending, which increased from \$10.1 billion in 2003 to around \$21.6 billion in 2012 [159]. Additionally, evidence shows that innovative activities and expenditures experienced a decline from 26.7% to approximately 10.8% around 2011 during the global financial crisis period. Following this, there was an approximately 80% reduction in the reporting of IES from 2012 to 2013 according to content analysis. However, across both databases, the situation analysis indicated a subsequent upward trend in the adoption of IES starting from 2013.

Figure 8 illustrates the pattern of annual publications related to technologies contributing to IES. The connection between IES and individual contributing technologies is highlighted by the trend. It shows that behavioural reflective attributes closely align with recommendation tools, while DT have garnered the least attention. This trend confirms the potential for integrating these closely linked technologies. The slower development of interest in DT publications can be attributed to their first appearance/introduction in the 2000s [64], though there was a significant surge in 2018. This substantial increase in 2018 aligns with the acknowledgment of DT as one of the top 10 technological trends that year [86]. Additionally, we present the percentage contribution of various technologies to integrated energy services (IES) (see Figure 8). Notably, there was a substantial rise, with recommendation accounting for 53%, closely following by behavioural attributes at 45.3% between 2010 and 2019. This trend suggests that recommendation mechanisms driven by external rewards have the potential to encourage energy-efficient behaviours. Substantiating this assertion, a correlation coefficient of 0.911 further confirms a robust positive relationship.

Table 2: Search keywords [142].

IES	DT	Recommendations	Behavioural attributes
"innovation" AND "energy services"	"energy services" AND "digital twins"	"energy services" AND "recommendation"	"energy services" AND "consumer behaviour"

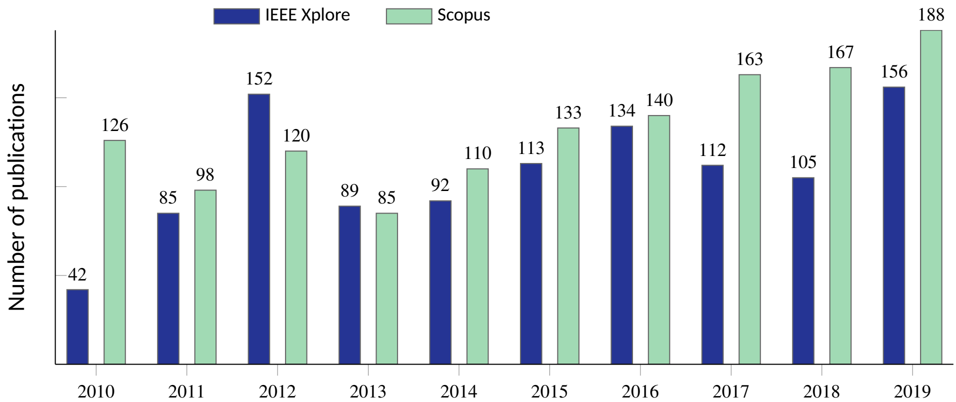


Figure 7: Yearly number of publications on IES in the period 2010-2019 from IEEE Xplore and Scopus databases [142].

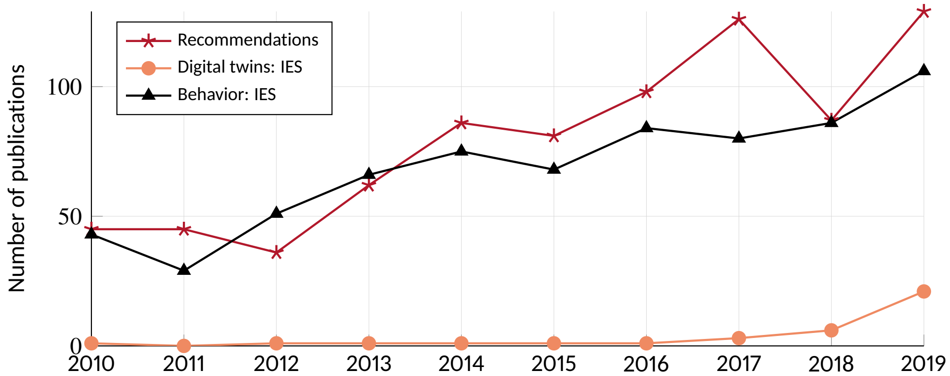


Figure 8: Visualization of yearly number of publications for IES contributing technologies in the period 2010-2019 from IEEE Xplore and Scopus databases [142].

2.7.2 Research design

This study aims to advocate for development of IES based on the integration of digital twin (DT) technology and non-invasive demand side recommendation services within smart energy grids as shown in Figure 6. The problem formulation involves a multiobjective optimization function along with constraints (refer to equations 1, 2 [144]). The objective function aims to minimize electric grid imports, subject to a set of constraints related to the loads and generators within the distributed grid network, including devices like water heaters, clothes dryers, and PV production systems. Additionally, in equation (2), the study intends to maximize the battery state of charge (SOC) subject to the available capacity $C(t)$ where battery current is denoted as I_b. The sampling period is $\mathrm{d}t$ and $\eta_b I_b$ represents the current efficiency for charging or maintaining a recommended SOC (approximately 30-40%) and mean temperature (between 20-30 $^\circ$C). Here, C_{max} is the maximum charge, and C_0 is the initial charge/capacity. Additional conditions for maximizing battery life include the battery's rated capacity (C-rate) discharge rate and the ambient charging temperature. Furthermore, equation 1 outlines the method for optimizing renewable energy self-consumption by minimizing grid imports. This is done in accordance with efficiency recommendations, focusing on PV production and electric grid imports allocated to the top-k energy-consuming appliances.

$$\begin{cases} \text{minimize} & \text{Electric grid imports} \\ \text{subject to} & \text{HVAC (recommendations)} \\ & \text{Li-ion battery (recommendations)} \\ & \text{PV production (recommendations)} \\ & \text{Electric grid export (recommendations)} \end{cases} \tag{1}$$

and

$$\begin{cases} \text{maximize} & \text{SOC} = \frac{C(t)}{C_{\max}} \times 100\% \\ \text{subject to} & C(t) = C_0 - \int_0^t \eta_b I_b \mathrm{d}t \\ & \text{Discharge C-rate (recommendations)} \\ & \text{Charging temperature (recommendations)}, \end{cases} \tag{2}$$

In this subsection, a hybrid digital twin model is constructed, focusing on the electrical components of smart grid end-users. This DT model mirrors the specifications of the reference smart grid system and promotes a decrease in overall energy consumption. Moreover, leveraging artificial intelligence (AI)-driven predictive analytics, smart meters, and IoT devices, smart grid assets were digitally recreated to anticipate the future trends of energy usage patterns of end-users. The proposed hybrid DT model forecast electricity asset behavior to identify changes in end-consumer behavior at the individual asset level. The predicted load behavior of end-users is then vectorized and scored to facilitate recommendation generation. This integration facilitates the provision of energy efficiency recommendations, thereby enhancing energy management, efficiency, and the utilization of renewable energy sources [144] (see Figures 5 and 6).

The hybrid DT approach was developed by modelling the electricity behavior of individual distributed grid entities (i.e. solar photovoltaics (PV), heating, ventilation, and air conditioning (HVAC) etc.). This method provides answer to research question R1 (see section 3). The proposed method combines domain-specific physics models with a machine learning approach based on a first-order ordinary differential equation (ODE) solver and a recurrent neural network (RNN) for electricity energy prediction in a DSM application on a distributed energy grid. The digital twin (DT) model is structured around the physical specifications and configurations of the reference system's components. Efficient simulation of this hybrid modeling approach for a smart grid scenario integrates various elements and systems, including electrical and information systems, necessitating a realistic and comprehensive multi-scale and multi-physics simulation and modeling approach. The developed hybrid DT model of individual electricity asset was further utilised to estimate future performance of electricity asset. The hybrid DT prediction outcomes were used as input for the ranking and recommendation operations.

Consumer electricity behavior was rated using a graph-based scoring approach to obtain an estimated description. Their energy behavior was modeled based on the transition frequency in the end-consumer's energy consumption profile. A time-varying energy flow is essential for describing the end-consumer energy profile, influencing the behavior graph's topology (with the rise and fall of attribute edges and nodes). The PageRank algorithm was utilized for scoring and ranking electricity consumers' behavior due to its scalability with limited datasets and its superior performance compared to other graph-based ranking models. This approach provides answer to research question R2. The proposed ranking method captures intrinsic data features by selecting those that strongly correlate with the desired load criteria to be scored. Given a graph G = (V, E), where E is the set of edges and V represents the vertices, the approach scores the highest consumption points across different load profiles (base (b), mid (m), and peak (p) load), while also considering the lowest consumption points for making recommendations (Details in section 4).

A demonstration of a demand-side conversational chatbot interface was built using generative pre-trained transformer (GPT) functionalities to serve the purpose of knowledge companion rather than mere knowledge instructor attributed with recommendation services to improve end-consumer engagement with DR solutions. Additionally, a questionnaire was utilized as the primary method to gather comprehensive data from participants on their attitudes and experiences. This approach provides answer to research question R3 (section 5). In the same vein, an XR interface was developed in section 6 to further enhance consumer interaction with proposed demand-side recommendations framework.

Lastly, the issues surrounding consumers' comfort was addressed using a multi-agent reinforcement-learning-based control technique that aims to improve the level of end consumers' comfort while using the developed DSM solution. The proposed technique provides answer to research question R4 (see section 7).

2.8 Motivation

Emerging technologies in the electricity smart grid, such as the phasor measurement unit (PMUs), advanced measuring infrastructure (AMI), and smart devices [104], are generating large volumes of data at an unprecedented rate. These datasets are rich in statistical properties that carry the digital signature of demand-side consumers. On one hand, this collection of big data holds immense possibility for aiding knowledge acquisition/extraction for grid optimization and demand-side management (i.e. deployment of behaviour adjustment/optimization programs using consumption pattern). On the other hand, analysing this data is posing a significant challenge and preventing the exploration of identified opportunities. In parallel to this, the economy of instant gratification and product customization gives energy consumers the feeling that their needs can be satisfied. By carefully modelling end-consumers beyond overall consumption profiles, a massive level of energy service customization can be achieved. This situation creates an avenue for the development of an advanced modelling and analytics platform and DSS service provision. Additionally, there is an urgent need to scale demand-side energy efficiency schemes. One way to achieve this is by using expensive large-scale sensor deployment for power system monitoring or using grid reinforcements, which may be considered cost prohibitive. However, the use of smart AI-powered algorithms and freely available smart meter data offers a cheaper solution that is rapidly scalable. This creates room for modelling electricity assets on an unprecedented scale, allowing for detailed/holistic access to understanding demand-side electricity behaviour. This study therefore presents an innovative electricity asset-level energy-efficient behaviour-modelling approach and a DSS for demand-side recommendation services. Consequently, with the rising adoption of smart home technologies in residential spaces and the emergence of substantial data streams enabling a deeper understanding of demand-side dynamics, along with considerable cost reductions in on-site generation and storage, as well as the increasing prevalence of self-consumption models and energy communities, coupled with the expanding decentralization of the energy system, it becomes evident that there is movement towards developing and implementing innovative energy services. These services aim to empower small residential consumers, transforming them into active participants and equal contributors within evolving energy markets that emphasize their inclusion in smart grid management strategies [9].

2.9 Discussion

This section, has examined the background, challenges, and literature associated with the topic of this thesis. The section further provides a rationale for undertaking the research work. It additionally articulates the appropriate research methods required for answering the general research question. One notable finding is that the literature revealed an upward trend in the adoption of IES. It is important to highlight that the analysis overall revealed a rise in the acceptance of IES within academic literature. Nevertheless, occasional disagreements regarding the best approach for developing IES persist in the energy industry [62]. This can be understood as a consequence of the extended period between the research and development stages, leading to extended payback periods for private investors. To address this issue, focused attention should be directed towards the need for the public sector to step in to alleviate this impact by ensuring sustainable development in innovative energy solutions and offering long-term funding opportunities. This two-pronged approach will help mitigate the challenges of funding innovation and reduce the impact of the developmental gap and its associated risks.

While the primary focus of this section revolves around comprehending IES through an in-depth review and content analysis of previous approaches, a notable benefit lies in its potential application as a catalyst or supplementary resource for investments in consumer-focused programs aimed at enhancing energy efficiency. We recognize the potential limitations associated with adoption barriers, which may include challenges linked to the introduction of new or emerging technologies, behavioural barriers, or past negative experiences with prior IES.

3 Modelling Technologies for Electricity Asset Profile

The goal of this section is to model electricity end-consumers based on the hybrid physics-machine learning (ML) scheme while identifying information gap components from the perspective of electricity consumers in order to improve sustainability and reduce electricity consumption. The information gap between consumers and the microgrid's individual components contributes to energy waste. This energy waste can be eliminated by generating energy-efficient advice using the proposed demand-side recommendation scheme [186].

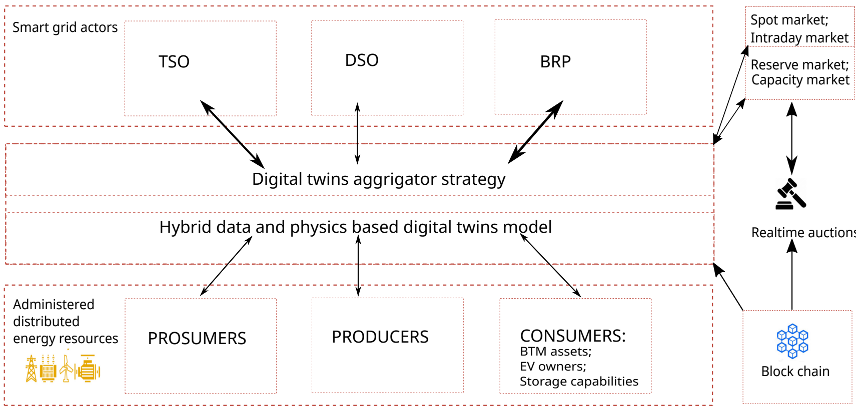


Figure 9: Roadmap for integration of digital twin assets for demand response within the framework of Energy 5.0 [140].

3.1 Digital twin modelling

To save energy, consumers and system operators are required to carryout analysis of various set-points and verify their impact on buildings in traditional demand-response schemes. This can be considered a difficult task from the perspective of an individual consumer or system operator. Another key limitation of the existing DR approach [189, 49, 16] is that consumers are often not given high priority in the planning phase of energy efficiency measures. They are instead treated as immovable objects during the formulation of building efficiency/optimization programs in most cases.

Again, while demand-response measures can be administered at the level of individual consumer profiles, it is important to note that the electricity consumers' influence on their electricity consumption also varies depending on which electrical appliance is being used. Consequently, a limitation can be placed on the amount of energy reduction that can be realized by simply optimizing around individual end-consumers [189, 164]. One solution to this problem is to presume that all electrical appliances are labelled, thereby allowing for the individual tracking of appliances while also indicating the amount of energy they are consuming [195]. Optimization around individual appliances, such as device-level modelling, rather than around individual consumers can be achieved with Industry 4.0.

The fourth industrial revolution embodies a number of key technologies: artificial intelligence (AI), internet of things capable devices [5], digital twins [175, 72], and big data that can assist in individual electricity device modelling. These are useful in engaging electricity consumers with smarter energy efficiency solutions, thereby creating the means for energy optimization at the level of microgrid electricity assets and beyond individual consumers. Industry 4.0 takes the lead in the efforts towards the decentralized connection of the grid asset and in turn the integration of energy-efficient models and services [186].

The trends in digitization and the consumer demand for high-quality and customized services indicate the need to reevaluate the DT concepts based on the inclusion of emerging enabling technologies [158], such as physics-informed machine learning. The benefits of creating a hybrid digital archetype of electricity devices is that processes can be streamlined using a data-driven machine-learning element capable of carrying out real-time updates using data while also gaining the advantage of devices' domain-specific physics laws and constraints.

From the perspective of end-consumers, knowledge about information associated with electricity components might be necessary for resolving end-consumers' conflicting objectives and decision-making process uncertainties [5]. Demand-side response policies aimed at reducing electricity consumption like those motivating electricity consumers are likely to benefit from the consumers' level of knowledge about their electricity consumption [13]. It is thus important to present them with accurate information that could be used to form a basis for their actions [195, 189]. Industry 4.0 creates means for all DT replicas of the electricity grid asset to be tracked, creating means to implement feedback schemes [164]. Feedback schemes built into DT models are capable of providing insights into the internal workings of the DT replicas thereby creating means to provide end-consumers with feedback using interfaces such as recommender systems. This way, consumers are acquainted with the uncertainties associated with their electricity demand while creating awareness of where their conservation efforts could be directed. In this case, an AI-powered personalized recommendation scheme [158] can serve as a decision support system that is capable of providing users with important information for managing their local energy systems [74]. Figure 9 presents an implementation road map for the integration of digital twin assets for demand response within the framework of Energy 5.0.

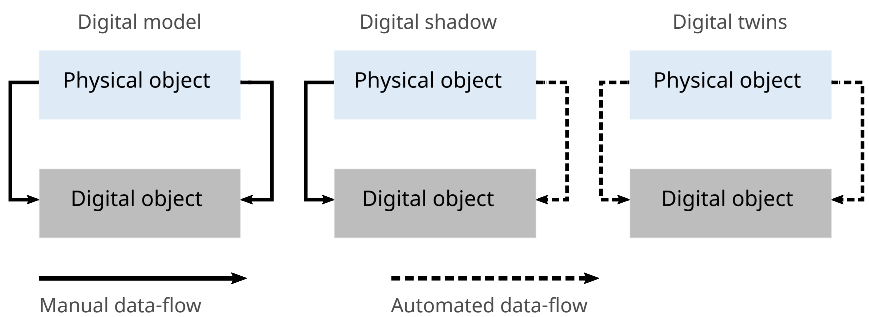


Figure 10: Schematics of digital model, shadow, and twin description of different levels of power system digitisation [144].

3.2 Non-intrusive load monitoring (NILM)

Individual appliance modelling based on NILM was achieved by estimating the individual appliance model from the overall electricity consumption time series or profile. The NILM load disaggregation approach allows for the easy estimation of the contribution of individual electricity asset/appliances to the overall consumption profile on the electricity grid. The proposed NILM model was developed using the combinatorial optimization (CO) algorithm. The CO algorithm attempts to identify each appliance's optimal state combination that minimizes the discrepancies between predicted and observed appliance aggregate power subject to a given appliance model [19]. The CO algorithm is described as:

$$\hat{x}_t^{(n)} = \underset{\hat{x}_t^{(n)}}{\arg\min} \left| \bar{y}_t - \sum_{n=1}^{N} \hat{y}_t^{(n)} \right|, \tag{3}$$

where $\bar{y}_t$ denotes the appliance n assigned power and $\hat{y}_t$ represents the actual power. The complexity of disaggregation for T time slices is $O(TKN)$, while the number of appliances is denoted as N, K is the number of appliance states.

3.3 Data-driven machine-learning model

A data-driven machine learning model is supported by an abundant supply of digital twin-related data combined with cutting-edge and easy-to-use open-source libraries/algorithms (e.g. OpenAI, Torch, and Tensorflow) alongside accessible computational resources (e.g. GPU, TPU, CPU). All of these aspects come together to drive the popularity of data-driven models. While physics-based models can be considered DT workhorses during the design stage, data-driven models are based on the general assumption that both known and unknown physics are underscored by data. As such, a data-driven model can be used to account for the physics of a system [158]. Again, a machine-learning based model utilizes a historical dataset to serve as input data to predict the future behavioural profile. The mathematical description of an example machine-learning-based recurrent neural network (RNN) approach is given as [39]:

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-d_y)), \tag{4}$$

where y denotes the historical data of electricity demand during a period of time (t) while f is the activation function. d_y represents the output of the feedback delay (FD) or lagged feedback.

An*artificial neural network* plays important role in the development of the black-box model of predictive DT used to forecast the behaviour of individual elements of the electricity grid asset. The description of the equation for the output function of the recurrent neural network (RNN) model based on the nonlinear autoregressive model (NAR) is given as:

$$\begin{aligned} h(t) &= \phi(Ux(t) + Wh(t+1)) \\ y(t) &= \varphi(Vh(t)), \end{aligned} \tag{5}$$

where $h(t)$ represents the hidden state, U,V and W are connection weight matrices and $x(t)$ is input, ϕ and φ stand for non-linear transformation function.

3.4 Physics-based model

This subsection contains a description of the models representing different classes of loads and their computational representations alongside the numeric solutions governing their energy behaviour. The description of electrical power P [W] passing through the terminals of an electrical element is determined by a product of current A and voltage U_{BA} and can be expressed as:

$$P = U_{BA}A. \tag{6}$$

The electricity energy E [J] passing through an electrical element can be presented as the integral of the power:

$$E = \int_{t_a}^{t_b} P\mathrm{d}t, \tag{7}$$

where t_a and t_b depict the beginning and end of the power flow's time interval, respectively.

Battery physics model: The battery model helps to obtain a dynamic comparison of the actual asset with the physical model. The battery modelling approach helps to address the battery lifetime and performance prediction issues. For example, in lithium iron (Li-ion) batteries, such modelling approach describes the voltage response to a current load over the cell's lifetime and the cell's resistance/capacity evolution [196]. The key element describing the battery capacity is presented as: [197]

$$C = C_0 e^{k\frac{iT_c}{t_i}}. \tag{8}$$

Furthermore, the battery degradation in relation to battery capacity is given as:

$$L = 1 - (1 - L^{'})e^{k\frac{iT_c}{t_i}}, \tag{9}$$

where T_c represents the cell temperature, and t_i is the charge time per cycle, $L^{'}$ represents the initial battery lifetime, and i denotes the cycle number. Again, L is battery lifetime, k is assigned a value 0.13, and f_d characterizes the linearized rate of degradation per time per cycle, which is presented as:

$$f_d = f_d\,(t, \delta, \sigma, T_c)\,. \tag{10}$$

An equivalent expression of empirically obtained estimates of f_d has been presented as [197]:

$$f_d = \frac{kT_c i}{t}. \tag{11}$$

PV physics model The electricity data associated with solar PV keenly depend on solar irradiation φ, the cell/ambient temperature T of the PV array, and the measured surface area of the PV systems S. The output power of the solar photovoltaic is modelled as [123]:

$$P_{pv} = \eta S_\varphi\,(1 - 0.005(T_a + 25))\,, \tag{12}$$

where η is the PV conservation efficiency. Again, φ, S, T, and η are important quantities that determine the amount of extracted power from solar irradiation.

Boiler and heat transfer physics model:

$$\dot{Q} = y\dot{Q}_0\frac{\eta}{\eta_0}, \tag{13}$$

$$\eta = \frac{\dot{Q}}{Q_f}. \tag{14}$$

Heat pump physics model: The associated physics model representing the heat pump system can be described as follows [187, 113]:

$$Q_h = Q_c + Q_{e^-}, \tag{15}$$

where Q_h depicts the condenser's hot side, while the cold side is represented as Q_c. The electricity energy utilized for compression is expressed as Q_{e^-}.

$$COP_h = \frac{P_h}{P_{e^-}} = \frac{Q_h}{Q_{e^-}}, \tag{16}$$

where COP_h represents the temperature coefficient of performance (COP), which is the ratio of heating thermal power presented as P_h to compressor electric power denoted as P_{e^-}.

$$Q_{HeatingDemand} = \dot{m}_w C_p \left(T_{w,sup} - T_{w,Ret}\right) \tag{17}$$

Following the previously described heat equation (see equation (15)), additional variables associated with geothermal heat pump simulation are the following [187]: the maximum heating power $P_{\max}$ was assigned a value of 10 [kW] and can be considered in association with the outdoor temperature assigned a value of -6 [$^{\circ}$C]. The computation of the heating demand and COP was based on equations (17) and (16), respectively. The the ground thermodynamic properties are depicted as C_p, with assigned values of 2000 [J/kg/K] and 2150 [kg/m3]). $\dot{m}_w$ is mass flow rate, while $T_{w,sup}$ is supply fluid temperature and $T_{w,Ret}$ is returned fluid temperature. S_d is the space domain specification with an assigned value of 40×40 [m2], while d is the space domain specification with an assigned value of 20 [m]. A reduction in numeric integration error can be assured by setting the stable time-step t as high, with an assigned maximum value of 3600 [s].

Air filter clogging physics model: The heating, ventilation, and air conditioning (HVAC) air-filter pressure drop can be responsible for the increased energy consumption and the drop in level of cooling satisfaction and efficiency. It is thus essential to model it. In other cases, maintenance of the HVAC system can be overlooked, which can result in serious consequences. A formal description of the model of the HVAC air filter in relation to the fan electricity consumption and air quality vis-a-vis the quality of outdoor air concentration is presented in equations (18) and (19) as follows [187, 188]:

$$m = Q_v \nabla t (C_e - C_s)\,[\mu g] \tag{18}$$

and

$$V \times \frac{\mathrm{d}C}{\mathrm{d}t} = C_s Q_v - C Q_v, \tag{19}$$

where m represents the accumulated mass in the filter at each time step t. C represents the room's homogeneous air concentration, while C_s is the concentration of the supply air. Q_v is the outside air flow rate and V is the room volume.

The modelling and simulation stages were established based on multi-physics technologies due to the scale of complexities associated with the smart grid system. Consequently, it is of importance to not only consider the single physics field effect or one-dimensional data, but also pay attention to the effect of coupling multiple fields while also keeping an eye on the relationships between these multi-physics and multi-scale fields [175].

3.5 Hybrid digital twins modelling

Hybrid/physics-informed ML model: A hybrid model established from a combination of physics-based and data-driven approaches was established on the assumption that the complexities and uncertainties attributed to the energy system are known. Again, an analysis of existing states using a simplified mechanism model is required, where simplified constraints can be introduced in practical application. Such constraints makes it hard to develop a model that completely fulfils the performance requirements when applied to a complex environment. In a similar fashion, a solely data-driven approach can be problematic when considering the explanation relating to the complex laws of physics. As such, neither a solely data-driven nor a physics modelling approach may be considered satisfactory for representing energy system intelligence [175, 158]. Subject to these inadequacies, a physics-guided machine learning (PGML) model promises to reduce model prediction uncertainties based on the infusion of physics-based elements at the simplified model intermediate layer [150].

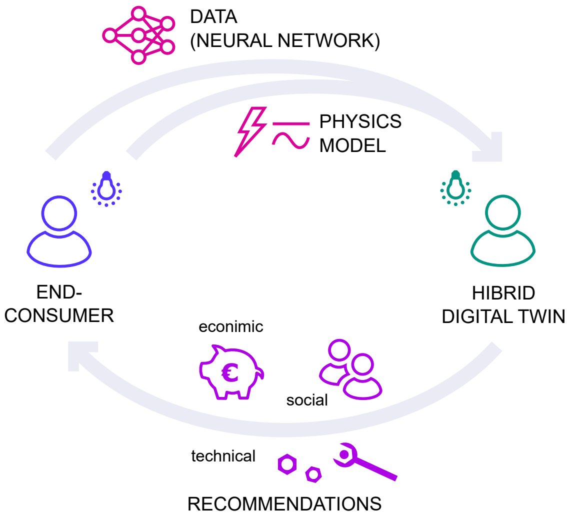


Figure 11: Digital twin framework for recommendation of energy efficiency services [144].

The prescribed hybrid DTs were developed based on an example approach using the ordinary differential equation (ODE) method to integrate the physics models of electricity assets (e.g. heating devices, battery) to reflect electricity devices' real-time status and machine-learning based prediction of future profiles (details in Figure 12) [175].

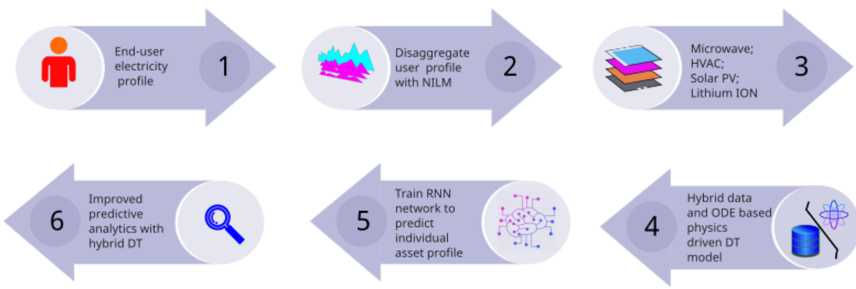


Figure 12: Process of building hybrid digital twins of individual electricity assets.

3.6 Consumer load prediction

Predictive digital twins: Behaviour forecasting was used to determine deviations in end-consumers' overall electricity profile, which can be seen as a combination of the individual asset-level profile using the proposed hybrid DT model. The combinatorial optimization (CO) algorithm (see equation (3)) was employed as an NILM technique for desegregating overall consumption profiles into component/devices for DT modelling used for asset-level prediction. Deviation in predicted behaviour compared to observed behaviour is used to determine changes that have occurred in the behaviour of the end-consumer.

In order to accurately present end-consumers with efficiency recommendations, changes in the state/behaviour of electricity assets must be estimated. Additionally, prediction of future load profiles is needed to optimize the operation of the microgrid. Hence, the hybrid DT model can be applicable for the prediction of responses associated with the microgrid asset. Again, after the forecast of the end-consumer load profile, deviations in behaviour were observed using metrics such as the MSE compared to the observed electricity asset profile. The total electricity consumption dataset (i.e. contributed by all selected assets) was windowed on an hourly basis between 01:00 and 24:00, which amounts to 24 individual data points. The predicted profile of an electricity end-consumer was further vectorised and scored so as to generate appropriate recommendations.

3.7 Evaluation metrics/framework

The evaluation metrics adopted for the study were used to identify changes in the predicted profile of the hybrid digital twins of individual devices compared to the baseline physics model. A formal description of the described metrics is presented in Table 3. Additionally, the indicator for identifying the difference between the observed and predicted profiles includes mean squared error (MSE) and mean absolute error (MAE), while the goodness of fit with respect to performance rating [39] (see Table 3) was determined using R-squared (coefficient of determination), where N represents the complete training set and p_i denotes the deliberate information estimation. Again, the actual value of consumption is denoted as q_i, and $\bar{q}_i$ represents the mean of the actual values of the N dataset.

Table 3: Mathematical equation of valuation metrics [144].

Metrics	Equation
Root mean squared error (RMSE)	$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2}$
Mean squared error (MSE)	$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2$
Mean absolute error (MAE)	$\text{MAE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert p_i - q_i\rvert}$
R-squared (R^2)	$R^2 = 1 - \frac{\sum(p_i-q_i)^2}{\sum(p_i-\bar{q}_i)^2}$
Mean absolute percentage error (MAPE)	$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\lvert\frac{p_i-q_i}{p_i}\rvert$

3.8 Experimental results

This section discusses the result of experiments that comprise the result associated with predictive hybrid DT and rank recommendation systems towards ensuring load/BESS profile optimization.

Figure 13 presents an overview of the experimentation dataset. This dataset comprises building net electricity consumption, particulate matter (PM) 2.5, and solar PV. The dataset associated with annual outdoor PM2.5 hourly measured concentration was obtained from Airparif [187, 188, 76], while the dataset associated with modelling lithium-iron battery storage was obtained from the NASA dataset [121]. Pecan Street and the reference energy disaggregation dataset (REDD) open-source data were utilized for overall dwelling electricity consumption and disaggregation of load profile [89, 125]. The described datasets were utilized in the modelling of the microgrid entities' hybrid DT.

Figure 14 represents the use of the NILM model for household-level load profile disaggregation into individual appliance utilization. The disaggregated dataset is further pre-

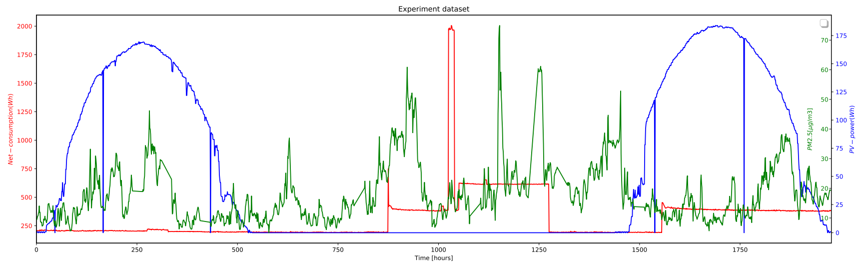


Figure 13: Experiment dataset comprising PM2.5, solar PV generations, and net electricity consumption profile for duration of 2000-minute simulation timestep [144].

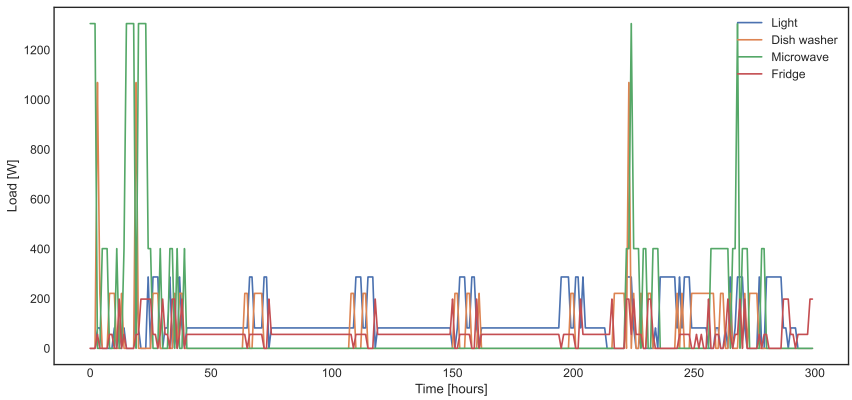


Figure 14: Illustration of disaggregated consumption data for modelling electricity general appliance based on the NILM model [144].

sented to RNN models to recreate the hybrid DT model of appliance with the support of ODE. This modelling technique ensures that individual appliance models can be estimated from a time series representation of a household's overall energy consumption.

3.8.1 Hybrid digital twin model-based real-time and predictive analytics

This subsection describes the prediction outcomes of the modelled hybrid DT. Figures 15-17 depict various case studies describing the hybrid DT modelling of different devices obtained from overall load profile, comprising assets such as solar PV, Li-ion battery, and HVAC air filter, respectively modelled based on physics laws/constraints and observation data. Figure 15 is a visualization of the comparison of the solar PV hybrid DT model and the outcomes of the physics baseline model. This model permits the prediction of various trends in the solar PV profile that could be useful in identifying variations in performance in the case of possible damage, with consequences such as reduction in production. Notable parameters used in solar PV modelling include the measured PV array area of $S = 100$ and conversion efficiency of $\eta = 0.5$ or 50%. Additionally, Figure 16 presents a comparison of a hybrid DT model with its counterpart physical model for Li-ion battery capacity. Another identical scenario representing the prediction of a HVAC air filter was presented in Figure 17, which predicts changes in the behaviour of HVAC filters and the associated energy consumption. It important to model HVAC systems as this plays a crucial role in the protection of humans and equipment from airborne pollutants. Additionally, it is important to pay attention to long-term operation/energy costs in air filter selection. For instance, the long term operation costs of a standard pleated filter may be ten times more expensive than its acquisition cost. A significant drop in air filter pressure can impact annual energy consumption and cost [112]. In comparison to energy-efficient air filters, the value can amount to about 4-5 times more than the cost of acquisition. Furthermore, about 81% of the total life-cycle cost of filters can be attributed to operating costs that are usually higher than the investment (18%), maintenance, and disposal costs (1%). Based on a life-cycle cost analysis of air filters, energy-efficient filters hold promises of improved/high energy conservation and reduced costs without the need for additional investments [101]. Again, to improve the efficiency of the filters and energy consumption, technologies such as photo-catalytic oxidation and non-thermal plasma photo-catalysis promise improved indoor air quality alongside improved energy efficiency [101].

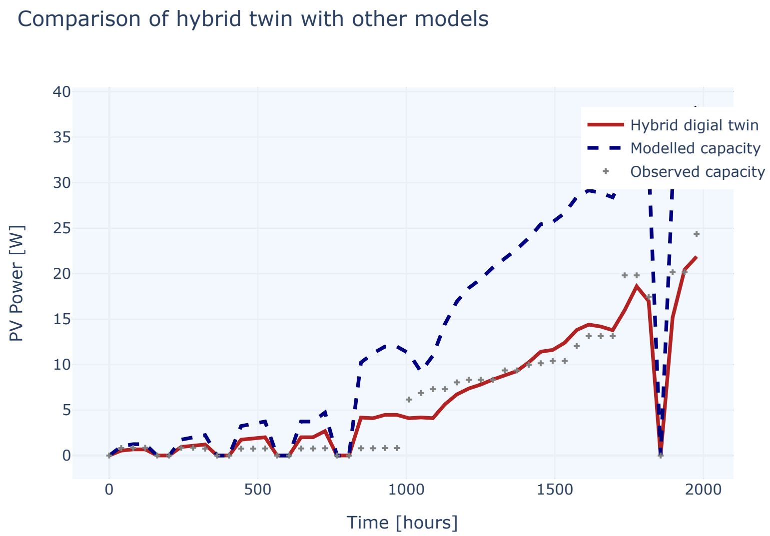


Figure 15: Comparison of hybrid digital twin vs. physics model for solar PV with a 2000-hour time range [144].

Figure 18a visualizes the weekly concentration of particulate matter and the consequent drop in indoor air filter pressure modelled based on an assigned filter value of $mc = 30$ [g]. For the purpose of this study, the assigned value represents the critical mass of particulate matter pollutants that must be attained/present in the filter before a filter replacement is required and accumulated mass can be reset to zero.

Figure 18b describes the hourly power consumption of the HVAC air filter estimated from the filter clogging and filter pressure drop depicted in Figure 18a. Air filters perform an important role in HVAC systems due to their functions associated with equipment protection from dust or the removal of airborne pollutants [187]. In most cases, the maintenance of HVAC systems can be overlooked, which could significantly impact the system. Figure 18b investigates HVAC air filter clogging alongside the fan power consumption effect, and the efficiency of air filtration in relation to the measured PM2.5 [101]. Additionally, Figure 19(a) and (b) is the correlation of the concentration of annual PM2.5-based soiling with the PV systems' solar irradiation degradation and re-normalized energy

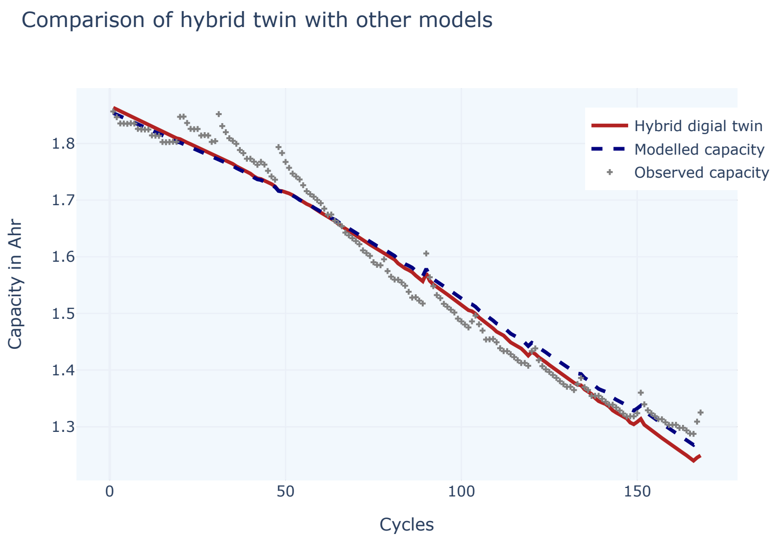


Figure 16: Comparison of hybrid digital twin vs. physics model for Li-ion over a 160-hour charge cycle [144].

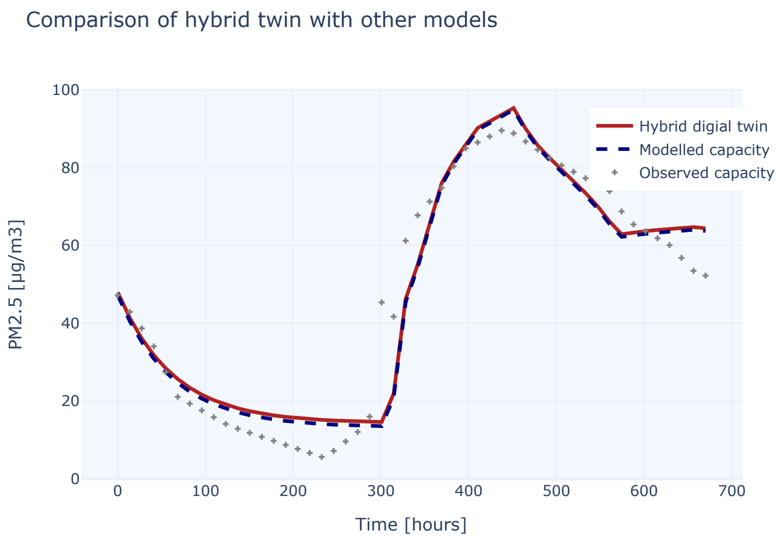
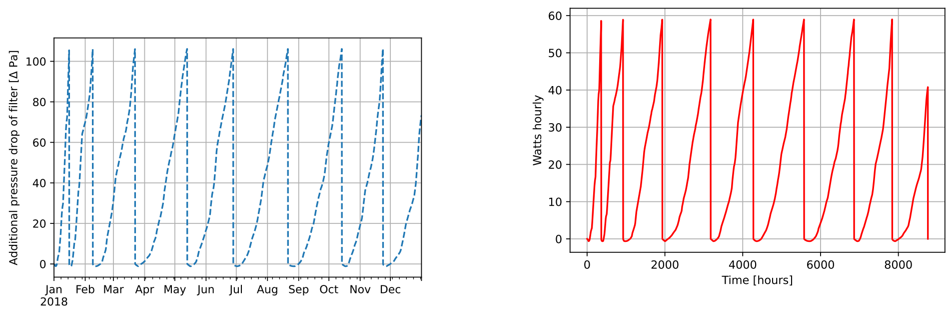


Figure 17: Comparison hybrid digital twin vs. physics model for HVAC air quality with a 700-hour time range [144].



(a) Air filter mass pressure drop due to clogging

(b) Estimated HVAC air filter hourly power consumption due to filter pressure drop/clogging

Figure 18: HVAC air filter pressure drop and equivalent additional power consumption (a) Air filter mass pressure drop due to clogging, (b) Estimated HVAC air filter hourly power consumption due to filter pressure drop/clogging [144].

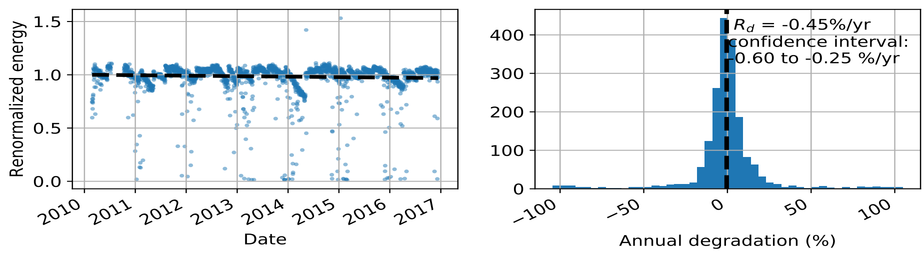


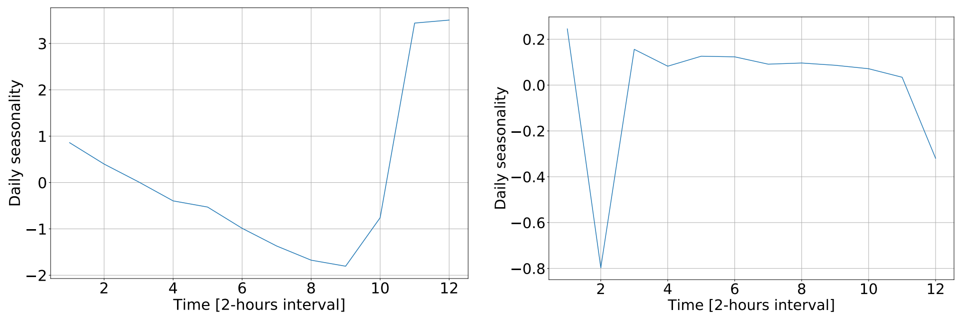
Figure 19: Solar PV soiling rate-based degradation result and renormalized energy due to PM2.5 (a) Renormalized energy subject to PV soiling rate (left), (b) Solar PV power output degradation result subject to effects of PM2.5 (right) [144].

production $[W/m^2]$. This outcome depicts a -0.45% degradation rate in the quantity of energy produced by the deployed solar PV subject to PM2.5 pollution.

These results (i.e. Figures 18 and 19) promise to help pre-informed end-users in regard to the status of the solar PV hourly generation of power, the HVAC air filter, and consumption alongside the use of predictive models such as hybrid DT (see Figs. 15 and 17) in the determination of future profiles *a priori* for ranking and recommendation provision. The recommendation provision can be utilized to maintain assets (e.g. improving solar generation by cleaning the surface of solar PV). A number of factors, such as performance loss rate, electricity price variation, and cleaning cost, can be utilized for the determination of the optimal frequency of annual PV cleaning. Figure 19(b) depicts the profit acquired from the mitigation of PV soiling in the upcoming year based on annual revenue compared to the unmitigated soiling scenario [115, 200]. It is vital to provide users with this information as it helps to extend the useful lives of assets (solar PV, HVAC systems), which by extension influences distributed grid operations and planning and cash flow.

Seasonality analysis: Energy consumption exhibits intricate seasonal patterns, requiring the consideration of various trends and seasonality aspects, such as hourly, daily, and weekly components [58]. Figure 20(a) illustrates the recurring seasonal pattern in the decomposed time series of the HVAC air filter DT signal. Likewise, Figure 20(b) showcases the seasonal trend observed in solar PV data.

Network training, model selection and validation This section examines the validation



(a) HVAC Air filter mass seasonality trend

(b) Solar PV seasonality trend

Figure 20: Seasonality analysis of selected microgrid asset (a) HVAC air filter mass seasonality trend, (b) Solar PV seasonality trend [144].

and selection of the proposed hybrid physics-AI DT models. The training of the AI machine-learning models spans a period of over 100 epochs, while convergence between training and validation scores were observed. Table 4 depicts the computed loss function using MAE model performance estimation (learning curve) with selected microgrid assets. The results after 100 epochs following the fitting of a hybrid DT model further revealed low error (i.e. MAE) scores for air filters (0.2), microwave ovens (0.3), and Li-ion (0.1) in comparison to geothermal heat pumps (HP) (2.5). It is important to note that MAE helps to quantify the discrepancies between the predicted and actual device profiles; the higher the accuracy, the closer the MAE result to zero.

Table 4: Comparison of MAE valuation metrics for the various models [144].

Model	**Training**	**Validated**
Solar PV	0	0
Microwave	0.60	0.30
Li-ion	0.02	0.03
Geothermal HP	2.00	2.50
Air filter	0.20	0.20

Network hyperparameter optimization (HPO): In our research, we focused on two sets of hyperparameters requiring adjustment. Firstly, the model design hyperparameters are associated with the structure of the deep learning (DL) model. The DL model's complexity is influenced by factors such as the number of hidden layers and neurons within those layers. For our chosen DL model with an input shape of 1, both the first and second hidden layers consist of 64 nodes, and the output layer has 1 node. Selecting the appropriate loss function, in this case MSE, is crucial for the problem at hand, determining how errors are calculated. Additionally, the choice of activation function, such as rectified linear unit (ReLU), is essential for capturing nonlinear relationships in the data. Lastly, the optimizer, specifically adaptive moment estimation (Adam), is configured to adjust the DL model's weights during training. Secondly, the optimizer hyperparameters are associated with optimizing the training process. These parameters include the number of epochs set at 100 (epochs = 100), which determines the number of complete passes through the training data. The learning rate, denoted as $lr = 1 \times 10^{-3}$, defines the step size for updating the

DL model's weights, and the mini-batch size, set at 20 (batch-size= 20), determines the number of samples used in each iteration before the model's update.

3.9 Discussion

The response to research question R1 was provided in this section. The research question aimed to investigate how digital twin model of individual electricity asset can be configured towards achieving the goals of consumer-centric demand side management. Industry 4.0 and its consumer-centric successor Industry 5.0 are currently undergoing extensive discussion within the context of scientific, political, and entrepreneurial perspectives [194] when considered from the policy, legal, and regulatory perspectives. Additional policies encourage the transition of cities into sustainable or energy-efficient urban landscapes with significant penetration of transient renewable energy sources [56].

The concept of hybrid digital twins model of individual electricity asset for DSM purposes was further explored in this section. This approach guarantees high level of fidelity which benefits from data-driven machine-learning properties such as immediate model updates while also providing the benefits associated with domain-specific physical laws. This modelling approach is necessary for dealing with the failures of traditional models in cases of transient and distributed nature of RES and market shock scenarios.

A critical approach to evaluating hybrid DT models involved dividing the dataset into training and testing sets to validate the DT prediction models. The training set is utilized by the hybrid model to populate the database using historical energy consumption data. Study outcomes shows that hybrid Digital twins model predominantly outperforms traditional predictive modelling techniques leading to a smaller simulation-to-reality gap and improved prediction accuracy with 84.132% decrease in prediction error.

4 Demand-side Recommendation Services

This section aims to present a methodology for demand-side recommendation services suitable for instructing electricity end-consumers with energy-efficient tips for effecting DSM. This was conceptualised by ranking the prediction outcomes of the hybrid DT (see Section 3.5) using a graph-based scoring model.

4.1 Behaviour scoring

Ranking algorithms strive to arrange a set of items based on their pertinence to a given inquiry. Similarly to various search methods, the core of achieving optimal user energy behaviour relies on relevance ranking. Profound comprehension of the domain and advanced ranking algorithms plays a crucial role. The algorithms that diligently deduce a user's intent when consuming electricity are the ones that excel.

4.2 Graph-based ranking method

In this section, we review the theoretical framework for modelling and evaluating consumer electricity behaviour aimed at managing energy. Ranking algorithms, a well-explored domain in information retrieval, plays a pivotal role in accurately assessing the essential components of energy consumption data. Graph-based ranking algorithms such as PageRank, TrustRank, HITS, MC, and the Diffusion ranking model have been instrumental in this pursuit.

4.3 Consumer behaviour rating and recommendation

Consumer behaviour rating was realized using a graph-based scoring method for obtaining the estimation of consumer energy behaviour. In general, consumer behaviour can be modelled using transition frequencies associated with the electricity consumption profile/time series data of the end-user [138]. A description of end-consumers' energy profile can be obtained with time-varying energy flow, which plays a significant role in the evolution of behaviour graph topology (with the rise and fall of attribute nodes and edges). The PageRank algorithm is adopted for the intuitive ranking of electricity consumers' behaviour due to its tendencies to scale with a limited amount of data available for a scoring task without the need for training, while also outperforming other similar graph-based ranking algorithms [138]. Features that are intrinsic in the time series electricity data but correlate strongly with the scored desired load criteria were captured by ranking algorithm. A rating/transition matrix (see equation (20)) is obtained from the hybrid DT forecast of an individual asset profile (see Section 3). Equation 23 is the adopted scoring of interesting features/nodes (i.e. repetitive features) that correlates with the load criteria intended for scoring [138]. The ranking algorithm generates scores attributable to dominant load features. Load dwell time (or frequency) ensures that end-consumers are alerted about frequently occurring load profiles/levels.

The predicted consumption profiles associated with each asset were utilized to generate a rating matrix (see equation (20)). Each row of the transition matrix denotes an individual asset (e.g. generators, devices, BESS, or load levels) attributable to a consumer, while each column represents load profiles (e.g. base (b), mid (m), and peak (p) load). The graph-based ranking approach proves to be a promising technique for the prediction of energy transition behaviour [138], where consumer behaviour is formulated as a ranking problem [43] and can be illustrated as $G = (V, E)$. Here, E represents the set of edges and V the vertices. This approach intends to obtain the repetitive patterns of the highest/lowest point of consumption associated with the various load profiles [97] for the provision of recommendation services.

$$G_{M\times N} = \begin{bmatrix} b_{11} & m_{12} & \cdots & p_{1n} \\ b_{21} & m_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & m_{m2} & \cdots . & p_{mn} \end{bmatrix}. \tag{20}$$

A content/item-based filtering recommendation algorithm was utilized for the selection of adjustable loads that have been producing higher scores for the simulation time slot based on the proposed PageRank algorithm [176], following the application of TF-IDF for data vectorization in the recommendation provision. Term frequency-inverse document frequency (TF-IDF) was used to obtain the TF-IDF matrix or vector space model (VSM) from a consumer's energy profile. The vector's components represent the importance of certain load categories or their absence in certain load profiles. TF-IDF allows the vector representation of textual data as:

$$\text{TF-IDF} = \text{TF}(t,d) \cdot \text{IDF}, \tag{21}$$

where

$$\text{IDF} = \frac{1+n}{1+df(d,t)} + 1. \tag{22}$$

Here, IDF represents the inverse document frequency, TF is the term frequency, t is the term contained in document d, and n is the number of data points/profiles that were considered in a given simulation window. More elaborately, TF(t,d) represents the raw count/frequencies of term t in document d. PageRank can be defined as:

$$\text{PR}(V_i) = (1-d) + d\sum_{i=1}^{N} \frac{\text{PR}(V_i)}{N(V_i)}. \tag{23}$$

Here d represents the damping factor, N denotes the total number of nodes, while PR(v_i) determines the currently ranked load profile.

The implementation of the recommendation segment was achieved using the PageRank algorithm, where top-N energy efficiency tips were presented to end-consumers.

4.4 Recommendation

This section contains a description of the scores associated with the individual predicted asset profiles used in the generation of actionable recommendations. Figure 21a contains the PM2.5 air quality predictions generated by the hybrid DT of PM2.5 air quality in comparison to the physics baseline scenario for the HVAC profile. Figure 21b depicts the prediction outcome of the predicted capacity of the hybrid DT of Li-ion battery compared to the observed capacity [114]. The predicted profiles in Figure 21a and Figure 21b are ranked in-order to generate the necessary actionable recommendation.

The ranking scores depicted in Figure 22 show the scored result of the graph-based ranking algorithm for the overall energy behaviour of the microgrid end-consumer. Similar scores are generated for individual distributed grid entities (see example in Figure 21) used for downward ramping [176] and grid operation optimization. The result of the score generated from the PageRank model shows that the base load (low profile) score is low compared to either peak or mid load profiles, which both return identical score margins.

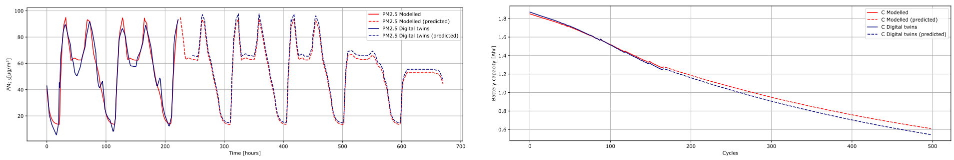
Algorithm 1 Recommendations for integrated microgrid load/BESS for downward load ramping

1: **Input**
2: Historical lists (set L), $L_1, L_2, \ldots, L_m$ of flexible loads
3: Temperature lists (set T_B), $T_1, T_2, \ldots, T_m$ of BESS
4: **Output**
5: Recommendations for all flexible loads
6: Recommendations for optimal charging voltage

7: Recommend all loads if dispatch order is larger than size of all flexible loads and charging voltage is within acceptable temperature margin and go to 8
8: Compute space separation `TF-IDF` between B_l, M_l, and P_l using (21)
9: **for** $k \leftarrow 1$ to $\text{Total\_number\_of\_FlexibleLoads}$ **do**
10: Remove list exceeding B_l
11: Remove list exceeding M_l
12: Remove list exceeding P_l
13: **end for**
14: **for** $k \leftarrow 1$ to $\text{Total\_number\_of\_FlexibleLoads}$ **do**
15: Compute scores obtained from ranking model using (23)
16: **end for**
17: **for** $k \leftarrow 1$ to $\text{Total\_number\_of\_BESS}$ **do**
18: Compute the optimal charging voltage associated with current ambient temperature
19: **end for**
20: Sort top-N flexible load based on ranking or scores
21: Recommend flexible loads with the highest rank until dispatch order is accomplished
22: Recommend update battery charge voltage
23: Construct and update new list Set B_l, M_l, and P_l; and Set T_B

In all, both mid and peak load profiles have been dominant in the simulated load scenarios, thus suggesting possible adjustments in end-user behaviour. Such adjustments may be to prevent the progression of mid towards peak and to encourage the progression of the peak profile towards low profile based on efficiency recommendation.

Figure 23 contains a description of a scored consumer energy profile rating distribution. The result shows the dominance of score 3.5 with the highest scoring density of about 3.0 in comparison to the other profiles with a score of 4.0 with a 0.2 rating density.



(a) Comparison of modelled hybrid digital twin vs. physics model forecast of PM2.5 for HVAC air filter

(b) Comparison of modelled hybrid digital twin vs. physics model forecast of Li-ion battery capacity

Figure 21: Comparison of modelled hybrid digital twin vs. physics model for the prediction of: (a) HVAC air filter, and (b) Li-ion battery capacity [144].

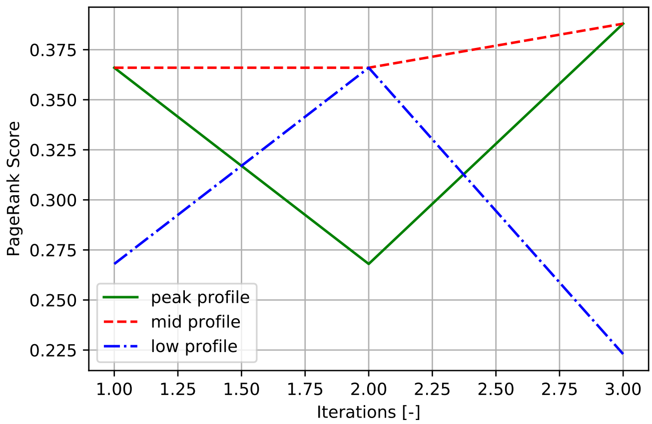


Figure 22: PageRank score of predicted disaggregated consumer energy profile for the period between 1 January to 1 February 2012 [144].

4.5 Experimental results

The transition matrix illustrates the distinct energy profile levels, such as base, medium, or peak, as visualized in Figure 24.

Figure 25 depicts the precision-recall curve (PRC) showcasing a comparative evaluation of different ranking models using similar test data. Precision-recall analysis indicates that PageRank and TrustRank exhibit outstanding performance compared to other ranking models. Specifically, the MC-rank model demonstrates superior precision at lower recall values (0.5) compared to other models. However, when examining higher recall values (0.8 or 1), its precision scores are lower overall in contrast to PageRank and TrustRank. This outcome suggests that PageRank and TrustRank are more effective in achieving superior ranking of consumption profiles.

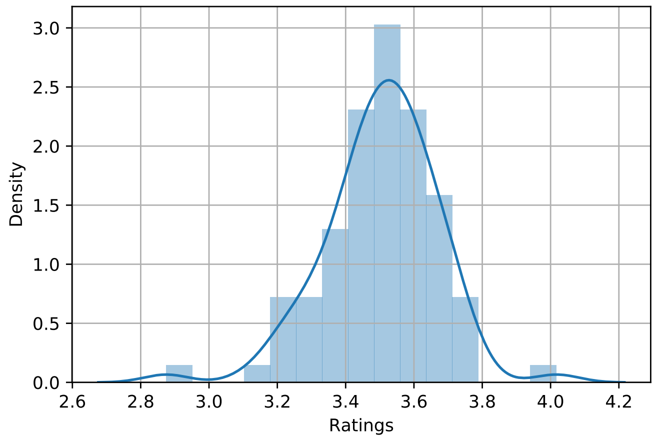


Figure 23: Rating distribution of scored consumer energy profile [144].

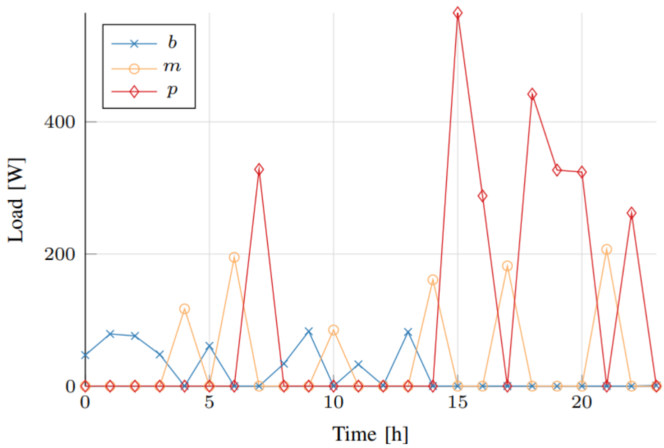


Figure 24: Visualization of typical electricity daily consumption profile for peak p, medium m, and baseline b load [137].

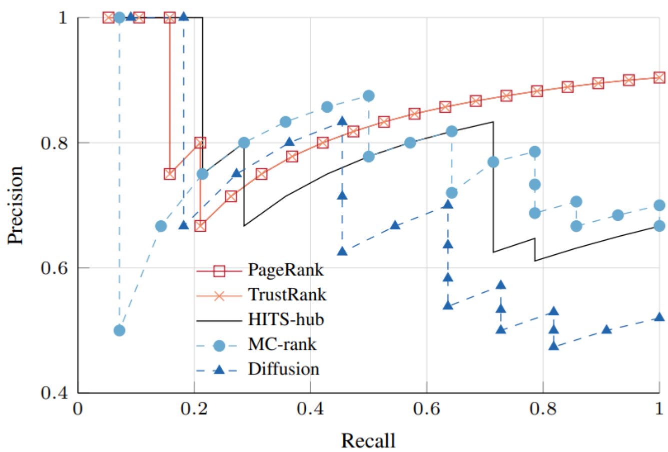


Figure 25: Precision vs recall plot of ranking models [137].

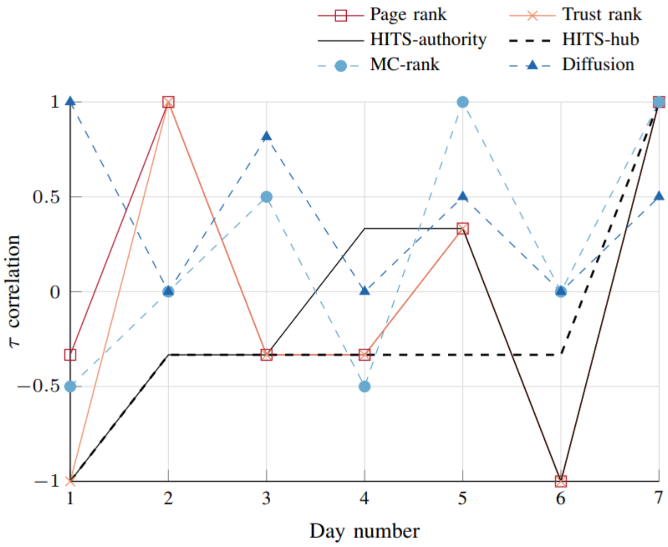


Figure 26: Visualization of Kendall-τ rank correlation curve for inter-day rank distribution for a seven-day period [137].

Figure 26 illustrates the level of linearity, denoted by τ, between inter-day rankings within the observed time frame (day 1 to day 7). The comparison resulted in a τ correlation coefficient of 1 ($6 < Day \leq 7$), indicating that most ranking models converge by day 7.

Table 5 is a representation of various efficiency recommendation tips targeting distinct microgrid assets. Recommendation tips targeting battery (BAT_R) were ranked 1.0, which highlights the important role of BESS in curtailing peak demand on the grid. An example recommendation tip (REC)-based DR directed towards microgrid entities (i.e. load) is presented in Table 5. Again, the table contains efficiency tips targeting ESS/battery, which helps end-users to improve demand-side electricity behaviour [45] and the performance of the battery. A number of factors such as thermal, electrical, or electrical abuse could cause damage to cells or the pack [52, 196]. Operations can be preemptively adjusted if consumers are given service notifications that help them to detect faults and prevent electric vehicle or battery catastrophic failure.

Notably, following the application of recommendation advice, end-users are able to implement the lessons learnt in DR operations. Table 6 contains a description of the sampling time of energy consumption attributable to a list of selected microgrid devices prior to the application of recommendation advice. Once recommendation tips are applied, the sampling time of individual devices is expected to reduce, which in turn promotes a reduction in overall electricity consumption.

4.6 Discussion

This section addresses research question R2. The section presents demand side recommendation scheme as alternative to invasive DR scheme associated with traditional DSM. Graph-based ranking model was utilized for estimating behaviour of individual electricity asset towards generating actionable energy efficiency recommendation. This approach is crucial as it enable consumer involvement in overseeing their electricity management in a highly scalable and non invasive manner.

To assess the recommender system's decision quality, various metrics such as MAE,

Table 5: *Energy service recommendation result [136].*

Category	Recommendation tips	Predicted score
BAT_R	Install renewable energy storage on site to reduce climate change levy payments	1.0000
REC	Install insulation in cavity/solid walls to increase thermal mass & reduce up to 1/3 heat loss	0.5588
EFF_R	Replace 5 of frequently used at-home lighting with ENERGY STAR energy-efficient bulbs to save 75	0.4771
BAT_R	Install battery storage to achieve up to 42% reduction in electricity demand	0.4713
REC	Install hot water thermostat to control water temperature from tap	0.4531
BAT_R	Operate/charge battery at optimal temperature 25°C to protect the battery and reduce demand	0.4259
REC	Replace HVAC filters to achieve up to 30% energy savings	0.42897
REC	Turn off appliances when not in use to save between 50 to 90 euros	0.4225
REC	Wash clothes at 30°C daily to save up to 10 euros annually	0.4201

RMSE, and cost-benefit analysis were employed. The recommendation system generates efficiency tips based on all dataset features. The study results indicate an approximate 24.5% decrease in net energy consumption following the implementation of the proposed non-invasive demand side recommendation framework [136].

Practical implications: The case studies demonstrated the efficacy of the suggested framework in offering tailored recommendations aimed at reducing electricity usage within microgrid energy management. It's essential to note that deploying this model in practical settings necessitates establishing communication channels between microgrid consumers and system operators or managers. Note-worthily, the adoption of innovative technologies, such as DT-based demand-side recommendation services, faces significant concerns, primarily linked to consumer reluctance due to potential disengagement and discomfort. While this article doesn't delve into this issue, a study by [136] explores mitigating discomfort and enhancing the adoption of demand-side recommendation services among end-consumers, addressing engagement challenges.

Table 6: Sampling frequency for load profile of end-user devices for 24-hour simulation period [136].

Appliances	**Sampling time per hour**	**Taxonomy category** [39]	**Energy (kWh)**
Computer	3(11:00 – 13:00)	Uncontrollable	1.50
Laptop	3(11:00 – 13:00)	Irregular scheduling	0.01
Electric stove	2(10:00 – 12:00)	Non-deferable	4.50
Power shower	1.5(8:00 – 19:00)	Non-deferable	7.50
Hair dryer	1(8:00)	Essential	3
Dishwasher	24(1:00 – 24:00)	-	2.50
Light	24(1:00 – 24:00)	Fixed	3
Fan	3(1:00 – 3:00)	Fixed	0.06
HVAC	24(1:00 – 24:00)	Regulatable	3.80
Refrigerator	24(1:00 – 24:00)	Hard load	2.50
Vacuum cleaner	3(6:00 – 8:00; 17:00)	Irregular scheduling	1.50
Electric space heater	3(2:00 – 3:00)	Delay tolerant-flexible	1.80
Central AC	7(12:00 – 18:00)	Regulatable	6.70
EV	5(22:00 – 3:00)	Battery assisted	10
Washing machine	5(1:00 – 2:00; 21:00 – 24:00)	Reschedulable	2.20
Clothes dryer	1(3:00 – 4:00)	Non-flexible deferrable	4
CRT TV	3(10:00; 14:00; 18:00)	General appliance	0.50
Microwave	24(1:00 – 24:00)	–	1.50

5 Demand-side conversational chatbot

This stage introduces a demonstration of a conversational chatbot interface built on generative pre-trained transformer (GPT) functionalities to serve the purpose of knowledge companion rather than mere knowledge instructor attributed with recommendation services to improve end-consumer engagement with DR solutions.

5.1 Conversational chatbots

The proposed chatbot was developed using the open-source OpenAI model generative pre-trained transformer 3 (GPT-3) in order to foster interaction between electricity end-consumers and the developed hybrid DT. Large language models such as OpenAI's GPT-3 are developed to mimic human language by being trained on large volumes of data samples taken from the internet. In this study, the output of the recommender system is utilized as an input prompt [92] for the chatbot, thus allowing the user to continue the discussion. This extended discussion allows users to clarify the suggested advice provided by the recommender system. GPT-3 is developed using a transformer neural network that comprises a feed-forward neural network (equation (25)), self attention, and an encoder. The result of the self attention was the sum of the product of the recommendation text vector and its associated scores. The encoder and decoder are connected using a multi-head attention [181] mechanism.

A set of input vector representations $(x_1, \ldots, x_n)$ is mapped by the encoder into a continuous sequence z $(z_1, \ldots, z_n)$ representation. An output signal $(y_1, \ldots, y_n)$ is generated by the decoder given the sequence z. At each step, the model is auto-regressive and the next symbol is produced by consuming previously output symbols as an additional input. The transformer overall architecture is based on a stack of self-attention (see equation (24)) and fully connected layers of point-wise encoder-decoder network given as:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V. \tag{24}$$

Here, the attention function is determined as a set of queries that is packed together into a matrix Q and the key and value is composed into matrices K and V. The dimension of keys is determined as d_k.

$$FF(x) = \max(0, xW_1 + b_1)W_2 + b_2, \tag{25}$$

where $FF(x)$ determines the feed-forward neural network, x represents the input vector that is multiplied by the specific weight and produces the weighted input. b is constant termed bias.

Intent modelling: The analysis of intent was used to trigger an associated feedback from the chatbot capable of helping with the further clarification of recommendation tips presented to end-consumers. For instance, if a recommendation tip suggests 'Save energy by changing HVAC filter' to users, words like 'filter', 'HVAC' and 'save-energy' are triggered based on key-wording spotting and synonym identification and thus help the conventional chatbot to better customize responses that may be satisfactory to the needs of end-users [24].

5.2 Consumer engagement index (EI)

A formal description of the metrics for the evaluation of consumer engagement was introduced as customer engagement scores. The customer engagement scores attributable to the demand-side recommender chatbot were calculated as a ratio of the total electricity end-user engagement with top-N recommendations to the total number of recommendations received by electricity end-users within the timestamp under review (description in equation (26)). Additionally, the metric is associated with the understanding of consumers' likelihood of extending their engagement with the developed demand-side recommendation framework. The engagement index (EI) is used to formalise the developed metric and is computed as:

$$\mathrm{EI} = \frac{R}{A \times T} \times 100. \tag{26}$$

Here, R represents the total number of reactions from end-users to recommendations within the period T under review and A denotes the total number of recommendation advice.

End-user interview and observations: A major objective of the study is to understand electricity end-users' engagement, which could be inferred from the collected feedback associated with user behaviour. Key elements of behaviour feedback can be defined as:

1. Dwell-time dataset used as proxy for consumer engagements
2. Mouse click
3. Conversational chatbot engagement

Additionally, an end-user study was conducted to understand the impact of demand-side recommender chat-bots on stakeholders' (i.e. electricity end-users) engagement with the recommendation framework. This was achieved based on the collection of data associated with the demand-side recommendation prompts that can be further associated with a number of microgrid assets/devices. Furthermore, a number of participant totalling 14 (aged between 20 and 50) who are residents of the Tallinn University of Technology Cybernetic building were recruited to participate in the study. The participants were presented with randomly sampled top-N recommendation prompts towards engaging the chatbot. Electricity end-user behaviour around the recommendation prompts (baselines) was compared against extended conversation around conversational chatbot prompts initiated from the baseline recommendation prompts in order to validate the proposed framework. Table 8 describes participant demographic characteristics that comprise gender and age. The following (three) questions are presented to participants with responses captured for further analysis:

- Q1: Will you click the recommendation prompt after seeing the advice prompt?
- Q2: Will you click the recommendation prompt after becoming aware of the DR recommendation chatbot?
- Q3: Which recommendation prompt is most attractive for engaging the DR recommendation chatbot?

The use of questionnaire was adopted to augment other usability methods, including the selected user study [199] evaluation methods described earlier comprising online (live user studies i.e. click-through rates (CTR)) and offline (explicit rating) techniques for validating conversational recommendation chatbot engagement performance. The user-centric evaluation method [199] adopted was based on end- user specific conversations with devices/asset chatbots.

5.3 Experimental results

The summarised results of measured electricity end-user characteristics are shown in Table 7. The results revealed that there was an around 228% increase in user dwell-time and a 68.7% increase in the click rate while interacting with the conversational chatbot, showing the potentials of the chatbot in encouraging end-users to further engage with the demand-side recommendation framework. Table 9 contains a description of the results of the end-users' EI with the recommendation chatbot. The results show an around 69% increase in end-user engagement with demand-side recommendation advice in comparison to the baseline scenario.

Table 7: Descriptive statistics of chatbot in increasing recommendation click rate and the number of pieces of advice clicked on by consumers [141].

	Recommendation tips		Chatbot		% Increase
	Mean	Std.	Mean	Std.	
# Click	7.545	3.115	12.727	3.250	68.675
# Dwell-time	1.175	0.661	3.877	1.491	228.077

Table 8: Participant demographic characteristics [141].

Age	20-24 (1, 7%)	25-29 (6, 43%)	Gender	Male	11 (78.60%)
	30-34 (4, 29%)	35-39 (1, 7%)		Female	3 (21.40 %)
	40-44 (1, 7%)	44-49 (1, 7%)			

Table 9: Engagement index (EI) of chatbot and recommender system based on consumer click rate [141].

	Recommendation tips	Recommendation + Chatbot	% Increase
EI	34.583	58.333	68.675

Statistical significance test: The result of the analysis shows that the t-statistic value (-3.19921) and p-value of p=.00497 significantly support the hypothesis that demand-side conversational chatbot technology amplifies consumer engagement with the demand-side recommendation framework. A statistical significance of $p<0.5$ shows the strong potential of the chatbot for improving end-user engagement with the proposed demand-side recommendation framework.

5.3.1 Application integration

Conversational chatbot technology: The final developed standard application interface is depicted in Figure 27 based on the integration of an NLP-based chatbot interface and the top-N recommendation tips (details in Table 5) interface that helps to further clarify efficiency recommendations (baseline).

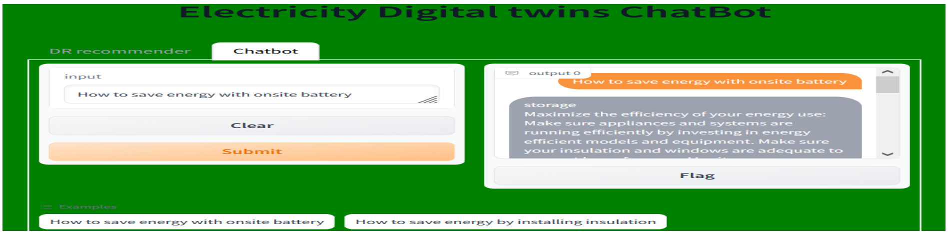


Figure 27: Illustrative example of conversational agent dialogue between consumer and chatbot based on efficiency recommendation prompts [92, 141].

5.4 Discussion

This section provides answer to research question R3. The research question aim to investigate the role of conversational chatbot technology in mitigation of electricity consumer disengagement with DSM programs. The section introduced an innovative conversational chatbot for demand-side recommendations, aiding non-technical electricity consumers in making decisions for demand-response (DR) operations. It leverages behaviour predictions from hybrid DTs of individual electricity assets, dynamically expanding the capabilities of the demand-side recommender system. The research showcases a case study involving the use of a GPT-3 chatbot that assists consumers in better comprehending the recommended energy efficiency tips. Additionally, the study further contributed to the understanding of how consumer disengagement can be mitigated.

To address the research question, we conducted a comprehensive analysis that explores the key factors and underlying mechanisms involved surrounding consumer engagement using the developed EI metrics. The results show an around 69% increase in end-user engagement with demand-side recommendation advice using EI metrics. Further outcome of the analysis indicated statistical significance, with a t-statistic value of -3.19921 and a p-value of $p=.00497$. These findings strongly support the hypothesis that the conversational chatbot significantly enhances consumer engagement with the demand-side recommendation scheme. The p-value of less than 0.5 underscores the substantial impact of the chatbot in improving user engagement with the proposed demand-side recommendation scheme.

6 Extended Reality

This section describes the integration of mixed-reality application with the proposed demand side recommendation framework.

6.1 Mixed-reality-based energy management environment

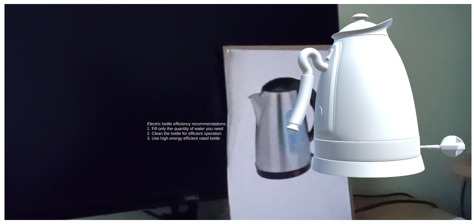
Insufficient planning and visualization of uncertainties driven by data and ineffective decision-making methods are two significant challenges in smart grids. These obstacles can be tackled through extended reality (XR) solutions. The research in XR has greatly benefited from the evolution of IT associated with smart grid advancements, including technologies for data capturing, IoT, wireless sensor networks, mobile hardware, GPS, and other related technologies [190]. Despite these advancements, visualization techniques are perceived as weak links in energy management (EM) schemes, requiring further enhancements to align with the integration of newer technologies. A study [170] highlighted that a key challenge hindering the deployment of advanced analytical models, such as digital twins (DTs), in smart EM systems is the lack of available virtual reality (VR) and integrated dynamic simulation technologies. There are lingering questions about the most effective methods to enhance the decision-making abilities of energy stakeholders [190].

Integrated with visual methods, virtual reality (VR) in energy management (EM) solutions holds substantial promise for enhancing the effectiveness of demand-response initiatives [94]. Traditional methods have a limitation in not encompassing consumers' engagement within a 3D energy space. The extension of EM visualization from 2D to 3D, as demonstrated by [68], reveals the potential for novel services and products aimed at EM. In order to assess the XR-based interface, a tangible test environment was created to enhance user intuition and energy awareness [80]. This enabled the representation of the physical environment and virtual data simultaneously, providing users with a real-time grasp of real-world information. Work [103] introduced intelligent financial data to comprehend market dynamics within the energy sector. Additionally, [152] outlined three VR-centred visualization techniques for intuitively depicting energy flow.

Mixed reality environment: Immersive technology such as virtual reality (VR) is a computer-generated environment that simulates a lifelike experience, allowing interaction through specialized electronic equipment. It primarily relies on interactive 3D graphics, user interfaces, and visual simulation (VS), presenting essential data and analyses using graphical languages within immersive settings [117]. In Figure 28, an XR-oriented mobile system designed to enhance mixed-reality interaction experiences by incorporating DT predictions and demand-side recommendation feedback into mixed-reality environment was introduced. This approach offers the advantage of introducing a physical asset such as an electric kettle while allowing end-consumers to interact freely not only with virtual objects but also with physical assets/devices. We illustrate how this system supports three categories of applications across the mixed-reality spectrum [102]:

- Entirely virtual objects, such as electric kettles, with demand-side recommendation service-generated efficiency tips are presented when end-consumers interact with the target asset using the mixed-reality application
- Virtual objects augmented through passive asset/devices integrated with mixed-reality application
- Augmented devices with virtual behaviours

(a) Electric kettle



(b) 3D model of electric kettle and top-N energy efficiency recommendations

Figure 28: Integration of mixed-reality environment and electricity efficiency recommendation feedback for electric kettle (a) Electric kettle, (b) 3D model of electric kettle and associated top-N efficiency recommendations.

6.2 Discussion

This section contributes to research question R3. It examined how XR can be used to improve consumer engagement by providing platform for the integration of dynamic simulation technologies. The section demonstrated how DR services can incorporate XR's capability to provide immersive experiences for customer engagement enhancement and to foster stronger relationships. The section further addresses issues associated with the integration of extended reality into the demand side recommendation framework. The utilization of high-fidelity virtual asset's DT representation was equally considered. The study further enhanced the understanding of strategies to mitigate consumer disengagement vis-avis the use of demand side recommendation services and energy users' 3D simulated experience.

7 Multi-agent Reinforcement Learning Control

Demand-response reinforcement learning control scheme: The proposed control strategy was developed based on a demand-response simulation platform using reinforcement learning (RL) agents developed using the OpenAI Gym environment (see GitHub repository [185]). The cooling and heating associated dateset was obtained either from building or surrogate models. Controllable power supply and storage modules such as thermal energy storage, air-to-water heat pumps, and batteries were developed in the OpenAI Gym framework. Again, the model of building heating and cooling loads was developed using the OpenAI Gym environment [183], which provides possibilities for microgrid energy simulation at the building level. The simulator adopts a physical reduced order and geometric 3D-model approach to estimate heating and cooling loads in buildings. The internal heat gain resulting from solar irradiation and the activities of the occupants of the building resulting in internal heat gain were also handled by the model. The building model was based on a single thermal zone, which accounts for the heating and cooling energy storage of different devices. The RL model uses a model-free and agent-based control approach that can learn based on interaction with the environment it plans to control and can be described using the Markov decision process (MDP), which is made up of a state S and an action A in combination with the transitional probabilities for transitioning between states $P : S \times A \times S \in [0,1]$.

$$V^{\Pi}(S) = \sum \Pi(S,a) \sum \mathrm{P}^{a}_{ss'} \left[\mathrm{R}^{a}_{ss'} + \gamma V^{\Pi}\left(S^{'}\right)\right]. \tag{27}$$

The agent's goal is to attempt to maximize the expected cumulative sum of the discounted reward within an infinite time horizon.

We start by giving a definition of the key components of the DR problems in the development of the proposed control framework. Based on the description presented in Figure 29, a number of components representing energy demand (electricity loads), electricity supply system, and BESS were connected to the electricity grid. The reinforcement agent was adopted for coordinating storage devices and the supply of electricity based on the fluctuation of price. Microgrid entities such as BESS and power supply devices constitute the simplest object attribute and are therefore located at the bottom of the bottom-up structural approach and instantiated and controlled by the building class. The simulation inherits from the super class of OpenAI Gym environment and is thus above the entities such as BESS and power supply object attribute. The RL-based demand-side recommendation simulation was conducted using a total of nine buildings with each comprising an individual RL agent based on the MARLISA configuration. Buildings were able to learn by interacting with one another towards the eventual minimization of electricity cost and by extension the overall microgrid electricity demand. Figure 29 comprises an illustration of the proposed demand-response-based reinforcement learning agent.

Here, $R^{a}_{ss'}$ is $r(s,a)$, which is the reward obtained following an action $a = \Pi(sk)$ that resulted in the transition from the current state $s \to s'$. $V^{\Pi}(S)$ is the expected result following a policy p starting from a state s. The future reward acquired from the discount factor is represented as $\gamma \in (0,1)$. Notably, model-free reinforcement learning models' transition probabilities are usually unknown. An example of a familiar model-free reinforcement learning model is Q-learning. A table containing the Q-values (the stat-action values) is used to represent the transition probabilities in tasks that comprise small state sets. Each table entry contains a state-action tuple (s,a), and the Q-value update can be represented as:

$$Q(S_t,a_t) \leftarrow (S_t,a_t) + \alpha\left[r(S_t,a_t) + \gamma_{a}^{\max} Q(S_{t+1},a_t)) - Q(S_t,a_t))\right]. \tag{28}$$

Here, $\alpha \in (0,1)$ denotes the learning rate that represents the degree to which old knowledge is updated by new knowledge, where s' denotes the next state. Q-values are depicted as the expected cumulative sum of discounted rewards following each action taken under each state using the greedy policy. Updates to policy are determined by Q-learning using past experience based on the off-policy approach, while other techniques might have been used to obtain such past experience. The tables of state-action-reward are fetched from the replay buffer where they are stored for iterative update operations as described in (28). The RL algorithm uses the Q-learning technique, which is trained and tuned in order to reduce the cost function [38].

Q-Learning agent design: The microgrid state is decided by the SOC of the battery and the balance of electricity demand. The continuous measure of state space is descritized using a different range of variables described in Algorithm 2. A description of discrete state space of battery charge (dSOC) is described in [87]. The *Reward* depends on a number of factors, such as battery state of charge (SOC) and the coverage of power demand. The supply of power coverage is achieved when 80% of the overall load demand to load is achieved. The objective is to maintain the maximum SOC value while trying to cover the amount of energy demand at the same time in a situation where the SOC of the battery is below the maximum value. The battery SOC (r_{SOC}) termed as reward is described as follows [87]:

$$r_{SOC} = \begin{cases} 1 & \text{SOC} > 90\% \\ -1 & \text{SOC} < 20\% \\ 0.1.soc_d t & 20\% \leq \text{SOC} \leq 90\% \end{cases} \tag{29}$$

Here, $soc_d t$ denotes a deviation in the rate of SOC acquired at different consecutive time slots. Additionally, SOC is continuous by nature, but for the sake of the study, SOC has been descritized into different ranges that include 1, 2, 3, and 4, and as such dSOC is represented as follows [87]:

$$\text{dSOC} = \begin{cases} 1, & \text{if } 0\% \leq \text{SOC} < 25\%, \\ 2, & \text{if } 25\% \leq \text{SOC} < 50\%, \\ 3, & \text{if } 50\% \leq \text{SOC} < 75\%, \\ 4, & \text{if } 75\% \leq \text{SOC} < 100\%. \end{cases} \tag{30}$$

7.1 Reinforcement learning based on the soft-actor critic approach

It is important to employ tabular Q-learning in order to control an environment that embodies continuous actions and states due to its potential to suffer from a dimensionality curse. An actor-critic RL method uses an artificial neural network to achieve state-action space generalization in which the current state is mapped to actions that the actor network estimates are optimal. Additionally, the critic network evaluates estimated actions by mapping them apace with Q-learning value states. An example of an off-policy model-free RL model [66] that is capable of reusing experience learned from example is the soft actor-critic (SAC) model. The SAC model is developed based on three key elements that include off-policy updates, maximization of training stability and efficient exploration entropy, and actor critic architecture. The SAC model is capable of learning three individual functions that include the value function V described in (31), the policy (the actor, and the soft Q-function (critic) [182]:

$$
\begin{aligned}
V(S_t) &= E_{at\sim\pi_\theta}\left[Q(S_t,a_t) - \alpha \log\theta(a_t|S_t)\right] \\
&= E_{at\sim\pi_\theta}\left[Q(S_t,a_t)\right] + \alpha E a_t \sim_\pi \theta[\log\theta(a_t|S_t)] \\
&= E_{at\sim\theta_\pi}\left[Q(S_t,a_t)\right] + \alpha H.
\end{aligned} \tag{31}
$$

Here, $H \geq 0$ is the Shannon entropy of policy π_θ, which represents the actions allowed to be taken by the agent's probability distribution for a given state S_t, while $\mathbb{E}_{at}$ denotes the expectation term. A deterministic policy $\pi_\theta = 0$ for all actions falls outside the optimal action a_t^* given that $\pi_\theta(a_t^*|S_t) = 1$ is represented as zero entropy. Policies with non-zero entropies are allowed to follow a more randomized action selection. The objective of SAC agents includes learning optimal stochastic policy π^* and can be represented as:

$$
\pi^* = \arg\max \sum_{t=0}^{T} E(S_t,a_t) \sim \rho_\pi \left[r(S_t,a_t) + \alpha H(\pi_\theta(\bullet|S_t))\right]. \tag{32}
$$

By choosing the policy's (mean distribution) expected action as the action of choice, the resulting optimal policy can be deterministic and can be considered the required ingredient for agent's evaluating after training. Given that $(S_t,a_t) \sim \rho_\pi$ is a state-action pair acquired from the agent's policy, $r(S_t,a_t)$ denotes the reward associated with a pair of given state-agent actions. The agent tries to maximise return as a result of adding the entropy term, while also maintaining random behaviour. Parameters representing critic networks are updated by minimizing the expected error J_Q between predicted and calculated Q-values (using iteration):

$$
J_Q = E(S_t,a_t) \sim D\left[\frac{1}{2}(Q_Q(S_t,a_t) - (r(S_t,a_t)) + \gamma E S_{t+1} \sim p\left[\mathrm{V}_Q^-(S_{t+1}))^2\right]\right]. \tag{33}
$$

The hyperparameter temperature expressed as $\alpha \in (0,1)$ in [192] should not be confused with the learning rate described in [98]. The importance of the entropy term is controlled by this parameter, which consequently allows the stochastics of learned $\alpha = 1$ to give priority to maintaining the maximum potential for stochastic behaviour capable of producing uniformly random behaviour while permitting $\alpha = 0$ to entirely ignore entropy as agents only focus on maximization of return and exclude exploration needs. This action produces a policy that is almost deterministic. This value was set to a constant $\alpha = 0.2$ [183] in this study.

7.2 Multi-agent reinforcement learning with iterative selective actions: MARLISA

This subsection describes the control application of the multi-agent reinforcement learning model for BESS. MARLISA extends the soft-actor critic (SAC) algorithm [129] (described in Section 7.1) functionalities, which facilitates the coordination of agents based on the sharing of reward and mutual information in a scalable, anonymous, and decentralized manner (details in Figure 29). Agents are required to share two variables that ensure the algorithm's scalability towards achieving coordination [182]. This is due to the fact that the number of variables used by individual agents does not increase as the number of agents increases. Therefore, the MARLISA model can be adopted for multi-agent problems in decentralization as can be found in the microgrid-coordinated load-shaping scenario. The MARLISA model was utilized for the control of chilled water and DHW storage [183, 182]. A set of control actions is transmitted by the RL agents as a set of control actions that returns a set of rewards and state s. The automatic constraints of the controller's action environment are used to keep the indoor temperature at a constant rate while ensuring a large enough supply of energy to the building to meet residential satisfaction before proceeding to store the remaining energy. During the implementation of the MARLISA model (details in Figure 29), each house on the microgrid is fitted with an RL agent with an individual objective that enables the individual agents to learn to coordinate among one another, irrespective of whether they lack knowledge of system dynamics or are initialized based on random policy. From the perspective of the power system, individual agents are required to learn to shape the overall load profile of the microgrid. Particularly, the evaluation of agents was based on their potential to reduce peak load, total ramping, and net annual demand, to maximize average daily load factor, and to reduce user dissatisfaction. The essential parameters of the multi-agent model used for experimentation include neural network architecture with 256×256 hidden layer size, batch size=256, decay rate $t = 5 \times 10^{-3}$, and ydiscount=0.99.

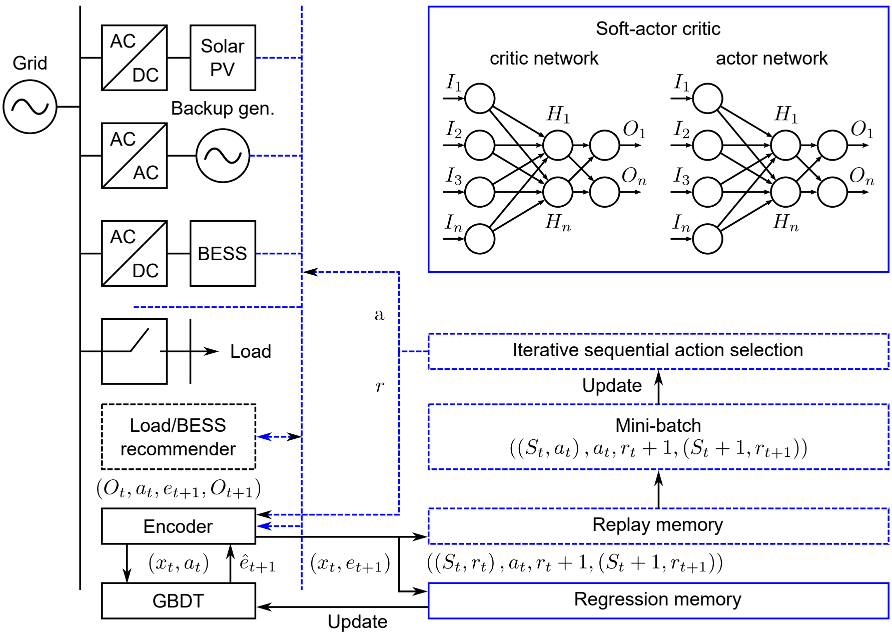


Figure 29: Simulation framework for MARLISA model in end-consumer energy-BESS recommender scheme based on microgrid network's key components [135].

In order to integrate MARLISA, Huber loss that is usually less prone to the outlier effect was utilized alongside layer normalization, with application to all critic network layers, owing to its potential to speed up the training of the network. Principal component analysis (PCA) was employed to achieve a 25% dimensionality reduction in encoded observation. Various reward structures were used to achieve the reward design for the experiment (details in (34)). Single target rewards r_i^1, r_i^2, and r_i^3, for instance, are used due to the fact that their value depends primarily on the building/agent's i net electricity consumption e_i. When more electricity is being consumed by the building than it generates $e_i < 0$, and when the building generates excess electricity $e_i > 0$, it is termed self-sufficient. The MARLISA agent partially collected reward function is based on the combination of individual agents' utilized net electricity e_i, and its collective component $\sum e_i$ is expressed as:

$$r_i^{MARL} = -\text{sign}(e_i)e_i^2 \min\left(0, \sum_{i=0}^{N} e_i\right). \tag{34}$$

This is the microgrid resident's overall electricity consumption that helps the agents share information among one another and thereby gives them rewards for accomplishing reduction in coordinated electricity demand. The empirical study outcomes presented in [183] show that the collective factor $\sum e_i$ with an exponential of 2 for e_i and an exponential of 1 produces an excellent result. The calculated mean and standard deviation at the beginning of the simulation and initiation of the random exploration phase following the result of reward collection was followed by the normalization of the collected reward alongside potential future reward.

According to the description by [182], the sign associated with r_i^{MARL} changes depending on the value of the individual and collected factors. The reward is negative When electricity is being consumed by the building from the grid, in the grid-connected microgrid, while the reward is positive when the building is generating more electricity than it is consuming. This is due to the fact that the building is contributing to the self-sufficiency of the microgrid. The agents' reward is zero when there is no electricity supplied from the grid and the microgrid is self-sufficient.

The collective reward described earlier provides a description of each microgrid agent's accurate goal description. However, this approach increases the stochasticity associated with the increased level of reward due to difficulties in each agent's ability to explain the changes associated with a collective reward factor. In order to provide a solution to this problem, a method of information sharing among all agents that allows them to make an accurate prediction of the next reward outlook under the current state subject to taking certain actions is given consideration. Each individual agent's received reward r_i^{MARL} keenly depends on both individual net energy consumption and the entire microgrid system's demand attribute. Consequently, a gradient-boosting decision tree (GBDT) model can be trained for an agent's action, representing individual buildings, and a normalized observation O_i subset is used to predict the net electricity consumption in building at the specified timestep following a given course of action.

The GBDT model's description at the mth step fits the decision tree $h_m(x)$ to an intermediate error term presented as the difference between actual (Pseudo residuals) and intermediate predicted value. The decision tree $h_m(x)$ model described as sum is presented in the following [57]:

$$h_m(x) = \sum_{j=1}^{j_m} b_{jm} 1 R_{jm}(x). \tag{35}$$

Here, j_m represents the number of leaves. The input space is divided into three partitions given as j_m distinct regions $R_{1m}, \ldots, R_{jm}m$ towards the prediction of actions in given regions. The coefficient b_{jm} denotes the prediction value within the region of R_{jm}. γ_m is selected by line search and multiplied by the coefficient b_{jm} in order to minimize the loss function. By choosing a different optimal value of γ_{jm} for the entire tree in place of the single γ_m and discarding the coefficient b_{jm}, the model can be updated as:

$$
\begin{aligned}
F_m(x) &= F_{m-1}(x) + \sum_{j=1}^{J_m} \gamma_{jm} 1 R_m(x), \\
\gamma_{jm} &= \arg\min \sum_{x_i \in R_{jm}}^{n} L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)).
\end{aligned}
\tag{36}
$$

To summarize, iterative sequencing action selection [182] was attained each time a list of agents that has been randomly sorted was created whenever the action selection function was called. Action a_{ik} is chosen by the first agent in the list, while its GBDT model predicts the quantity of energy consumption e_{kl} by the building consequent to the consideration of the action e_{kl} picked, followed by information sharing with the next agent. Notably, actions are not taken on an individual basis but kept on hold and finally taken as a set of all agents' collective action A.

Algorithm 2 Q-Learning

1: Initialise $Q(s,a)$ table
2: **for** each episode **do**
3: Initialise s
4: **for** each step of episode **do**
5: Based on policy derived from $Q(\varepsilon - \text{greedy})$ choose a from s
6: Take action a, observe r, $s^{'}$
7: Take action a, observe r, $s^{'}$
8: $Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha \left[r + \gamma_{\max} Q\left(s^{'}, a^{'}\right)\right]$
9: $s \leftarrow s^{'}$
10: **end for**
11: **end for**

Algorithm 2 describes Q-learning in the reinforcement learning model used for flexible loads and the BESS [93] control scheme.

7.3 Consumer comfort

The consumer comfort index (CCI), root mean squared error (RMSE) (for identifying behavioural changes), cost benefit analysis, and social cost of carbon estimation evaluation metrics were adopted in the experiments. Additionally, we compared the original consumption profile (baseline) of the microgrid consumers with the profile associated with the SAC and MARLISA control schemes using the previously described evaluation metrics. The results of the experiments were evaluated on the basis of the following parameters [132, 174]: (i) battery charge state and temperature, (ii) cost benefit analysis, (iii) social cost of carbon, (iv) RMSE, and (v) consumer comfort index:

$$
\text{CCI} = \frac{\text{Number of non-recommended hours of operation}}{\text{Total number of hours of period of operation}} \times 100. \tag{37}
$$

7.4 Experimental results

Tables 10 and 11 describe the tendencies of electricity end-consumers to experience some level of discomfort subject to the effect of the suggested energy efficiency advice/recommendation.

For example, a recommendation suggesting that consumers replace 25% of lighting sources (with a CFL or LED) is likely achieve a 50% reduction in electricity bills. Additionally, a recommendation suggestion that nudges consumers to adjust the air conditioners by a degree above 72 °F for a given period in order to achieve up to a 1 to 3% reduction in their bill may result in a level of discomfort in the cooling season. For instance, advising end-users to reduce the use of AC (12000BTU) from their acclimate seven-hour operation to smaller but more energy efficient AC (10000BTU), consumers are able to save up to 2050W (2.05 kW), which reduces electricity consumption while improving energy efficiency ratio (EER) from 3.69 to 8.33 but with a noteworthy 42.6% level of discomfort in only 24 hours as shown in Table 11. Similarly, a recommendation tip suggesting that end-consumers hand dry their clothes rather than use a drying cabinet (2.32 kWh) has significant potential to conserve energy and cost, but it is equally likely to decrease end-users level of comfort (see Table 11).

Table 13 shows the effect of the control scheme compared to the BUA/baseline or the scenario without DSM for a 120-hour simulation timeline. The results revealed that MARLISA achieved a reduction of up to 24.5% in peak electricity demand from 486.5 kW to 367.3 kW when compared to the baseline or the scenario without DSM, showing an overall reduction of up to 199.208 kW.

Finally, an analysis of benefits and avoidable operational costs was carried out in Table 13. The results describe the cost reduction in USD ($) for household consumers obtained from Eurostat [50] for the first half of 2021 based on an original electricity unit cost (flat tariff) of $0.24 per kWh or 0.22 € per kWh. The original electricity cost without the use of the DSM scheme for 486.50839 kW consumption amounted to $116.76201 per kWh. In comparison, using the proposed MARLISA RL control algorithm, end-consumers were able to achieve an approximately 24.5% cost reduction from $116.76201 to 88.152. In a similar manner, MARLISA outperformed SAC with a 1.259% higher electricity cost.

Table 10: Load hour reduction with demand-side recommendation scheme [135].

		Max load duration	
	Load rating (kWh)	Prior advice (h)	Post advice (h)
Heat pump	4.7	16 (1,...,11;20,...,24)	8 (8,...,11;20,...,24)
Central AC (4000BTU)	6.7	7 (12,...,18)	4 (12;14;16;18)
Drying cabinet	2.32	3 (1;21;23)	1 (1)
Power shower	7.5	1.5 (8;19)	0.083 (8)

7.5 Discussion

The answer to research question R4 was examined in this section. The section explores the application of multi-agent reinforcement-learning-based control techniques that aims to improve the level of end consumers' comfort while using the developed DSM solution. The section thus addresses issues associated with end consumers' discomfort using a novel CCI metrics to address the research question.

The results show up to 94.47% increase in end-user comfort level in certain loads while using the developed demand-side recommendation framework. Another significant finding of this study is that implementing the control scheme not only enhanced consumer comfort but also resulted in up to a 24.5% reduction in the net cost of electricity while

Table 11: Consumer comfort index with demand-side recommendation and multi-agent RL control scheme [135].

	Comfort level		
	Prior advice (%)	Post advice (%)	Increased % with RL + advice (%)
Heat pump	100	50	50
Central AC (4000BTU)	100	57.4	42.6
Drying cabinet	100	33	67
Power shower	100	5.53	94.47

Table 12: RL achieved scores for MARLISA and SAC baseline towards demand reduction [135].

	1-load factor	Net energy demand	Peak demand	CO2 emission
SAC	1.0967	1.008	1.0869	1.015
MARLISA	1.1268	0.9991	1.2045	1.007

Table 13: Benefit and avoided operational cost analysis for 120-hour simulation period [135].

	Peak load (kW)	Peak reduction with DSM (kW)	Reduction (%)
PV no BESS	374.56079	111.9476	23.0104
SAC	373.4	113.10839	23.249
MARLISA	367.3	119.20839	24.5028

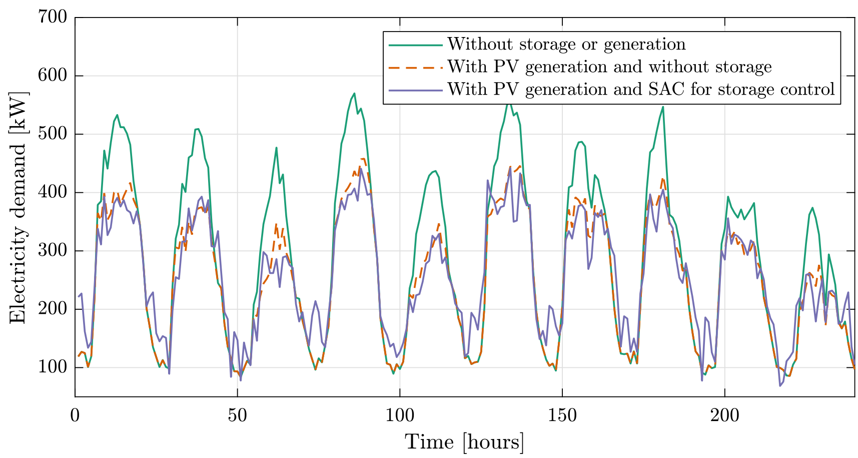


Figure 30: Plot of electricity demand without storage (kW), electricity demand with PV generation and without storage (kW); electricity demand with PV generation and soft-actor critic (SAC) scheme for storage control (kW) [135].

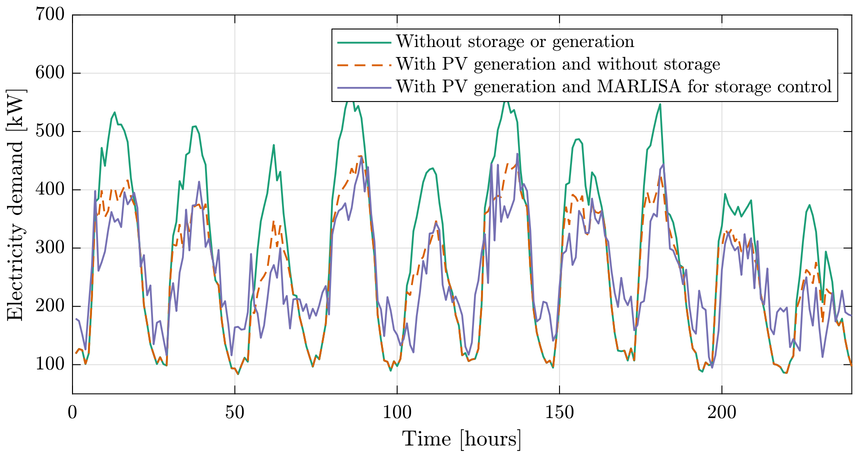
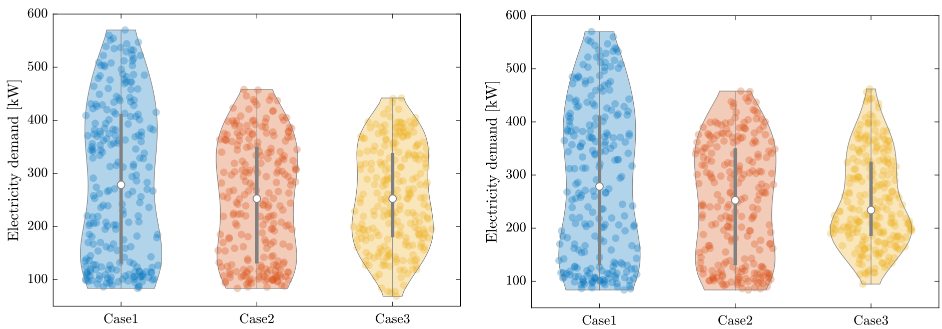


Figure 31: Plot of electricity demand without storage (kW), electricity demand with PV generation and without storage (kW); electricity demand with PV generation and MARLISA for storage control (kW) [135].



(a) SAC

(b) MARLISA

Figure 32: Plot of net electricity demand recorded for various scenarios; Case 1: without storage; Case 2: with PV generation and without storage; Case 3: with PV generation and SAC (left plot) or MARLISA (right plot) for storage control [135].

using the proposed control scheme.

Practical implications: The case studies demonstrated the framework's effectiveness in providing tailored recommendations for reducing electricity usage in microgrid energy management. Crucially, when implemented in the field, the model necessitates a communication channel within the microgrid connecting consumers and other microgrid entities. From the aggregators' standpoint, deploying this model is straightforward—providing them with an analysis log from prior cases and access to information about new scenarios is sufficient. From the consumers' viewpoint, the framework encounters few obstacles in its implementation, primarily focused on setting up communication channels to facilitate information flow. The methodology's implementation enables the delivery of recommendations to buildings or installations within the microgrid, detached from the specific approach each consumer employs in following these suggestions. Broadly, diverse application scenarios such as BEMS or end consumers' manual application approaches could be taken into account.

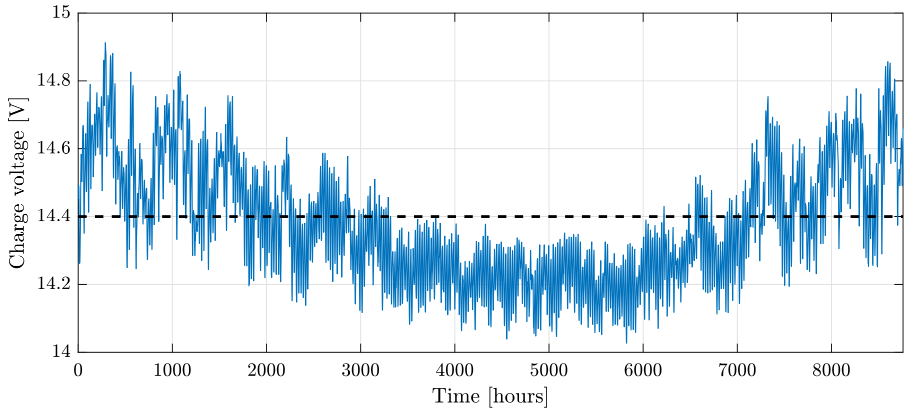


Figure 33: Temperature compensated voltage battery charging [135].

8 Conclusion and Future Plans

This thesis introduces the concept of an intelligent recommender system for innovative energy services, aiming to provide households or consumers with tailored and intelligent recommendations based on their asset-level energy usage predictions and other available metadata. Unlike the prevalent utility-focused approaches, we advocate placing consumers at the forefront by employing their digital twins instead of conventional end-consumer-based modelling methods. Recent technological advancements enable the development of solutions that cater to the needs of ordinary individuals.

In this research, the concept of an IES-based recommendation service was introduced, drawing from a comprehensive review and content analysis of prior methodologies. This study outlines the architecture of the proposed IES framework, offering energy-saving alternatives without necessitating significant lifestyle changes for consumers. Our observations revealed two prominent research trends. A thorough content analysis demonstrated a growing inclination towards adopting IES. The evolving landscape of distributed energy resources (DERs) and the emerging potential of IES provide a comprehensive framework that is useful for understanding the requirements needed for direct engagement at the independent asset (i.e., RES) level towards the electricity market's demand-response (DR) service provision.

First, a hybrid digital twin (DT) modelling architecture was presented as a solution to bridge communication gaps by directly linking end-consumer behind-the-meter (BTM) assets, transmission system operators (TSOs) and electricity consumers through DT representation of the electricity grid. This approach provides response to research question R1. The proof-of-concept for a multi-asset hybrid DT modelling system that integrates domain-specific physical constraints and laws to enhance prediction accuracy in DR electricity market applications. A non-intrusive load monitoring (NILM) approach was proposed for disaggregating overall consumers' load profile into individual asset contribution towards asset modelling. This study introduces an innovative approach employing an ensemble of hybrid digital twin (DT) asset models based on a combination of ordinary differential equation (ODE) physics engines and data-driven recurrent neural network (RNN) prediction methods. Papers I, IV, II, VII demonstrated hybrid digital twin, underscoring the importance of hybrid DT models at individual asset level. These studies assess the key DT characteristics relevant to DR solutions and lays the groundwork for deploying individual distributed grid assets in the demand-response market via their DT replicas. It also examines the current state of DT applications in DR with aim to eradicate inefficiencies inherent in current DR setups.

Following the DT modelling of individual electricity asset for real-time and predictive analytics functions, an innovative method involving a comparative analysis was employed to effectively assess graph-based ranking algorithms intended for eliciting and scoring consumer-focused energy behaviour towards the implementation of demand-side management solutions. This method addresses research question R2. An evaluation of accuracy demonstrated that both PageRank and TrustRank yielded commendable results as optimal measures for scoring energy savings. One advantage of this proposed unsupervised graph-based method is its reduced computational demand. Another significant benefit identified in the study was the ability of ranking algorithms to aptly model consumer behavioural transitions, contributing to effective DSM solutions. Additionally, a demand-side recommendation service was developed to provide the electricity end-consumer with actionable insight into their energy behaviour. This service was compiled using predictive and real-time analytics and the PageRank scoring algorithm. In paper III, a personalized consumer-centric recommendations based on ranking scheme was developed. Asset-level behaviour obtained from the hybrid DT models was scored to understand the prevalence of certain traits among consumers in order to generate recommendation tips that are likely to influence their future energy behaviour. Consequently, the developed adaptive demand-side recommender system was utilized to offer recommendations tailored for different microgrid entities (e.g., loads, generators).

A significant worry regarding innovative technologies like DT-based demand-side recommendation services involves adoption challenges. Two key factors contributing to consumer reluctance in adopting new technology/services are disengagement and the anticipated discomfort experienced by end-consumers. The thesis further introduces an innovative conversational chatbot aimed at aiding non-technical electricity consumers in enhancing their decision-making capabilities and their engagement with the developed demand-response (DR) framework. The chatbot operates by predicting behaviour through a hybrid digital twin (DT) modelling of individual electricity assets, dynamically extending the capabilities of the demand-side recommender system. The studies examined in publications VIII and IX include a case study showcasing the utilization of a GPT-3 chatbot that assists consumers in gaining a deeper understanding of the recommended energy efficiency strategies thereby providing answer to research question R3. Based on the preceding discussion, the thesis further provided a detailed approach focusing on utilizing Industry 4.0 digital twins and multi-agent reinforcement learning for recommendation strategies on the demand side, considering consumer comfort within decentralized power systems. To solve the problems of anticipated discomfort experienced by end-consumers as described in research question R4, the thesis introduced an implementation of a distinct multi-agent reinforcement learning controller dedicated to managing active battery energy storage system (BESS) technologies, distinctly separating them from loads that impact user comfort. Papers V and VI demonstrated key metrics underscoring the importance of consumer comfort in DR applications.

We conducted a comprehensive review of XR visualization techniques within the distribution grid across four distinct domains. Within each domain discussed, we delve into the essential components of power distribution using a modularized XR framework. Furthermore, we identify recommendations for integrating distribution grids with virtual schemes.

The primary contribution of the research lies in highlighting consumers as key actors in endeavors aimed at energy conservation, which is achieved through the adoption of innovative solutions stemming from recent advancements in recommender systems and DT technology. While the primary focus of this study revolves around comprehending IES through an in-depth review and content analysis of previous approaches and proof-of-concept developments using DT-based demand-side recommendation services, a notable benefit of the research lies in its potential application as a catalyst or supplementary resource for investments in consumer-focused programs aimed at enhancing energy efficiency.

This results of the findings from the in-depth review and content analysis of IES aligns with the study's goals, showing an approximate 83% rise in its implementation. Another notable trend involves the collection of IES-related technologies, where the content analysis exhibited a rising pattern observed in recommendation studies, yielding similar results to those found in behavioural attribute literature. This outcome further substantiates the idea that providing recommendations impacts energy behaviour. We believe these research trends largely stem from heightened awareness, increased research and development (R&D) investments, and various incentivized adoptions of IES-based DSM tools. These adoptions are often driven by economic, social, or psychological factors, as indicated in the literature. Based on the preceding discussion, the experimental results associated with the use of Industry 4.0 digital twins and multi-agent reinforcement learning for recommendation strategies on the demand side, considering consumer comfort within decentralized power systems, revealed a noteworthy 24.5% decrease in overall energy consumption and a remarkable 94% enhancement in comfort for certain loads. Furthermore, the study's outcomes show that the hybrid digital twin approach accomplished an impressive 84.132% reduction in prediction error, as measured by MSE metrics.

8.1 Future works

Considering what lies ahead, the potential applications of the developed models include the following:

- Research continuation: Further investigation into the chosen area of software science, often involving deeper exploration of specific subtopics, theories, or methodologies.
- Further studies or contributions: Continuing academic pursuits, contributing to further research, or exploring opportunities for teaching or industry involvement in the field of software science.
- Collaboration and networking: Engaging with peers, experts, or other researchers in the field for collaboration, feedback, and discussion of ideas.
- Application and implementation: Applying the acquired knowledge or proposed methodologies in relevant real-world scenarios or practical applications.

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Acknowledgements

I would like to express my deepest gratitude to my PhD supervisors Prof. Juri Belikov, and Prof. Eduard Petlenkov for their invaluable guidance, support, and mentorship throughout my doctoral journey. Their expertise, patience, and encouragement have been fundamental to my academic and personal growth. Their unwavering belief in my capabilities and their constructive feedback have not only shaped my research but have also inspired me to pursue excellence in all aspects of my work. I am profoundly thankful for their dedication, which has been instrumental in helping me navigate the challenges of this rigorous academic endeavor. It is an honor to have had the opportunity to learn from and work with such distinguished professionals. Thank you for investing your time and effort in my development and for contributing significantly to my success. I am particularly grateful to Prof. Juri Belikov for his pivotal roles in formulating my research topic.

Secondly, my profound thanks go to my co-authors from The Technion – Israel Institute of Technology, Prof. Yoash Levron, and Dr. Ram Machlev for their cooperative efforts in the course of development and refinement of publishable ideas.

My gratitude extends to my fellow doctoral candidates and colleagues, whose camaraderie, insights, and shared experiences have enriched my journey in ways immeasurable. The sense of community and mutual support within the school of Information Technologies, Tallinn University of Technology has been a source of strength and encouragement throughout the highs and lows of my PhD journey.

I thank my family for their immense support and prayers.

I extend my heartfelt thanks to the following organizations for their generous financial assistance throughout my PhD studies:

The PhD program resulting into this thesis was partly supported by the the Estonian Centre of Excellence in Energy Efficiency, ENER (grant TK230) funded by the Estonian Ministry of Education and Research and Estonian Research Council grants PRG658 and PRG1463.

I am also thankful for the financial support provided by Tallinn University of Technology through scholarships, grants, and assistantships. This financial assistance has been essential in allowing me to focus on my research and academic commitments without undue burden. Thank you, Tallinn University of Technology, for playing such a pivotal role in my academic and personal growth. I carry forward the values, knowledge, and skills I have gained here as I embark on the next phase of my professional life, inspired to make a meaningful impact in the world.

Lastly, I wish to acknowledge the broader university community, including the administrative and support staff, whose behind-the-scenes efforts ensure the smooth functioning of our institution. Your dedication to creating a conducive learning environment has not gone unnoticed.

Abiodun Emmanuel ONILE, 2024

Abstract

Innovative Energy Services based on Behavioural–Reflective–Attributes and Intelligent Recommendation Systems

In recent times, the escalating impact of urban climate change and the increasing demand for electrical energy have become pressing concerns. Broadly, electricity conservation strategies rely on efficient utilization. Yet, challenges arise due to consumers facing difficulties in executing these measures. In order to achieve the desired efficiency in energy usage, innovative solutions aimed at influencing the behavior of energy consumers are necessary. Personalized recommendations play a crucial role in stimulating behavioural changes among consumers, thereby contributing to sustainable advancements in energy efficiency.

Addressing this challenge, our study centers on innovative energy services reliant on intelligent recommendation systems and digital twins. We examine various trends related to modeling and the adoption of energy services, considering the positive connections between recommendation systems and the energy behaviour of consumers on the demand side. Through a comprehensive content analysis of leading research works in the IEEE Xplore and Scopus databases, our study validates the innovative use of data-driven twin technologies for demand-side recommendation services.

Industry 4.0 plays a role in end-consumers progression towards energy efficiency by enabling more sophisticated analytics and creating avenues for end-consumers and decentralized grid assets to be modeled similarly to their Digital Twin (DT) counterparts. This development opens pathways for asset-level analytics. This study introduces an innovative approach employing an ensemble of hybrid DT asset models, combining ordinary differential equation (ODE) physics engines and data-driven recurrent neural network (RNN) prediction methods. The emerging real-time information technology (IT) applications and innovative modeling of DT for individual electricity assets are disrupting this landscape. Particularly, in relation to integration of intermittent renewable energy sources which offers promising demand-response (DR) solutions, but also brings about emerging stability issues for the electricity grid. Similarly, aggregators are increasingly pivotal in the DR electricity market, yet they frequently grapple with substantial market monopolization and a lack of transparency by profiteering or taking advantage of transitive RES.

Additionally, following modelling of individual asset based predictive DT, this study introduces an novel graph-based ranking approach using PageRank model for demand side recommendation service provision.

There are specific scenarios where end-users might disregard recommended advice, contributing to a widening 'knowledge-action gap'. A demand-side recommender system, complemented by Generative Pre-trained Transformers (GPT) for a conversational chatbot interface technology and Extended Reality (XR) proves effective in engaging and extending end-consumer interest in recommended advice.

The novelty of this research lies in developing a new approach that enables individual end-user assets to contribute to demand-response initiatives.

Results from the study demonstrate that employing BESS through the multi-agent reinforcement learning control strategy yielded a maximum peak load reduction of approximately 24.5%, alongside a 94% and 69% improvement in comfort for specific loads and users engagement respectively. Furthermore, efficiency-related recommendations for BESS contributed to a linear reduction in peak load, surpassing the baseline scenario. The study's outcomes also show that the hybrid Digital Twin approach accomplished an impressive 84.132% reduction in prediction error, as measured by MSE metrics.

Kokkuvõte

Arukatel soovitussüsteemidel põhinevad uuenduslikud energiateenused

Eestikeelne kokkuvõte tehtud tööst. Tänu käsule `otherlanguage` saame kasutada täpitähti ja sõnad poolituvad vastavalt eesti keele reeglitele. Ingliskeelses tekstiosas peaksime kasutama LaTeXi käsklusi täpitähtede tekitamiseks.

Viimasel ajal on kliimamuutuste suurenev mõju ja suurenev nõudlus elektrienergia järele muutunud pakiliseks probleemiks. Laias laastus tuginevad elektrienergia säästmise strateegiad tõhusale kasutamisele. Siiski tekivad probleemid, kuna tarbijatel on nende meetmete rakendamisel raskusi. Soovitud tõhususe saavutamiseks energiakasutuses on vaja uuenduslikke lahendusi, mille eesmärk on mõjutada energiatarbijate käitumist. Isikupärastatud soovitused mängivad olulist rolli tarbijate käitumismuutuste stimuleerimisel, aidates seeläbi kaasa energiatõhususe jätkusuutlikule arengule.

Selle probleemi lahendamiseks keskendub meie uuring uuenduslikele energiateenustele, mis tuginevad intelligentsetele soovitussüsteemidele ja digitaalsetele kaksikutele. Me uurime erinevaid suundumusi, mis on seotud modelleerimise ja energiateenuste kasutuselevõtuga, võttes arvesse positiivseid seoseid soovitussüsteemide ja tarbijate energiakäitumise vahel nõudluse poolel. IEEE Xplore'i ja Scopuse andmebaaside tippteadustööde põhjaliku sisuanalüüsi kaudu kinnitab meie uuring andmepõhiste kaksikutehnoloogiate uuenduslikku kasutamist nõudluspoolsete soovitusteenuste jaoks.

Tööstus 4.0 mängib rolli lõpptarbijate liikumisel energiatõhususe suunas, võimaldades keerukamat analüüsi ja luues võimalusi lõpptarbijate ja detsentraliseeritud võrgu varade modelleerimiseks sarnaselt nende digitaalsete kaksikute (DT) vastanditega. See areng avab teed varade tasandi analüüsile. Käesolevas töös tutvustatakse uuenduslikku lähenemisviisi, milles kasutatakse hübriidseid DT-vara mudeleid, milles kombineeritakse tavalise diferentsiaalvõrrandi (ODE) füüsikamootoreid ja andmepõhiseid rekursiivseid neuronivõrgu (RNN) prognoosimeetodeid. Tekkivad reaalajas töötavad infotehnoloogia (IT) rakendused ja uuenduslikud DT-mudelid üksikute elektriseadmete jaoks häirivad seda maastikku. Eelkõige seoses taastuvate energiaallikate integreerimisega, mis pakub paljutõotavaid lahendusi nõudlusele reageerimiseks, kuid tekitab ka uusi probleeme elektrivõrgu stabiilsusega. Sarnaselt on agregaatoritel üha olulisem roll DR elektriturul, kuid nad võitlevad sageli märkimisväärse turumonopoli ja läbipaistvuse puudumisega, kuna nad teenivad kasumit või kasutavad ära taastuvate energiaallikate üleminekut.

Lisaks sellele tutvustatakse käesolevas uuringus pärast individuaalsetel varadel põhineva prognoosiva DT modelleerimist uudset graafipõhist järjestusmeetodit, mis kasutab PageRanki mudelit nõudluspoolse soovitusteenuse osutamiseks.

On konkreetseid stsenaariume, mille puhul lõppkasutajad võivad jätta soovitatud nõuanded tähelepanuta, mis aitab kaasa teadmiste ja meetmete vahelise lõhe suurenemisele. Nõud-luspoolne soovitussüsteem, mida täiendavad geneerilised eeltreenitud muundurid (GPT) vestlusliku juturobotiliidese tehnoloogia ja laiendatud reaalsus (XR), osutub tõhusaks lõpptarbija huvi äratamisel ja laiendamisel soovitatud nõuannete vastu.

Selle uurimistöö uudsus seisneb uue lähenemisviisi väljatöötamises, mis võimaldab üksikutel lõppkasutajatel anda oma panus nõudlusele reageerimise algatustesse.

Uuringu tulemused näitavad, et BESSi kasutamine mitme agendi tugevdava õppimise juhtimisstrateegia abil andis maksimaalse tippkoormuse vähenemise ligikaudu 24.5%, lisaks 94% ja 69% mugavuse paranemise vastavalt konkreetsete koormuste ja kasutajate kaasamise puhul. Lisaks sellele aitasid tõhususega seotud soovitused BESSi jaoks kaasa tippkoormuse lineaarsele vähenemisele, mis ületas baasstsenaariumi. Antud töö tulemused näitavad ka, et hübriidne digitaalne kaksikmeetod saavutas muljetavaldava 84.132% prognoosivea vähenemise, mõõdetuna MSE-meetrikaga.

Appendix 1

I

A. E. Onile, J. Belikov, and Y. Levron. Innovative energy services for behavioral-reflective attributes and intelligent recommender system. *In Proceedings of 2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe) – 10th International conference of IEEE PES ISGT Europe Conference, Virtual, The Hague, Netherlands, 2020*, 1(1):1–7, 2020

2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)
Virtual, October 26-28, 2020

Innovative Energy Services for Behavioral-Reflective Attributes and Intelligent Recommender System

Abiodun E. Onile, Juri Belikov
Department of Software Science
Tallinn University of Technology
Akadeemia tee 15a, 12618 Tallinn
Email: {abiodun.onile, juri.belikov}@taltech.ee

Yoash Levron
Andrew and Erna Viterbi Faculty of Electrical Engineering
Technion—Israel Institute of Technology
Haifa, 3200003, Israel
Email: yoashl@ee.technion.ac.il

***Abstract*—The European Union is promoting efficient use of energy through innovative energy services targeting improved consumer behavior. At a time when the value and preferences of consumers for better services provision continue to evolve, there is a need for tools and algorithms that reduce consumption cost while placing consumers as major player for reducing energy use. To improve our understandings on how consumers can better manage their energy, this study presents a concept of innovative energy services for behavioral-reflective attributes combined with intelligent recommender system, which shall help to optimize the energy profile by suggesting consumer-oriented recommendations.**

***Index Terms*—recommender system, innovative energy services, data analysis, feature engineering, policy**

I. Introduction

In the last decades, energy systems were in the focus of continuous monitoring and attention by individual households and large energy consumers to better manage their resources and determine consumption profiles using services provided by special consultants and experts. The energy consumption has however steadily increased in the EU leaving designated energy observers to play catch-up. This is majorly attributed to rapid innovation in the electronic industry and demand for quality services and comfort by consumers [1]. In light of these trends, the question is no longer whether consumers will be equipped with smart solutions, but rather how these integration will occur.

Innovative Energy Services are required to overcome challenges of inefficiency in the energy market. The current European Union efficiency drive (art 8) and the future Horizon Europe (cluster 5) programs encourage the development of programs allowing consumers to undergo energy audit, and provide incentives for implementing the resulting recommendations. On the contrary, consumers lack the expertise, capital, and time resources to implement the required conservation measures. A report presented by [2] indicates that Europe needs to develop investment strategies in energy efficiency [1]. Furthermore, there is urgent need to empower consumers through digitization and development of models for clean and efficient energy use. Information and Communication Technology infrastructure is being integrated into demand-side management to measure energy usage in real time, and to determine how energy is utilized in a more efficient way [3]. Although, the idea of non-intrusive load monitoring (NILM) has been vastly researched as it attempts to achieve load/appliance disaggregation, with potential application to utility based demand side management and provision of energy consumption information to consumers towards energy conservation. In spite decades of development, NILM is still faced with tremendous challenges relating to adaptability with various categories and sizes of appliances. Energy consumption in commercial, industrial, and residential sectors can be better managed using the emerging technologies of Big Data, Smart metering systems, and Internet of Things [4]. Another aspect to consider is rising interest in the use of mobile technologies and social applications recorded on a global scale, which creates an action oriented approach for the end user participation in the process of energy management. These applications help consumers to take decisions by analyzing their preferences or profiles. Understanding the behavior of inhabitants is important for defining energy consumption patterns, and can be essential feature in efforts directed to reduction of energy wastage [5]. It is however important to understand that a major challenge associated with the efficiency of the generated behavioral patterns is the ease of communication and interaction between the generated information and our physical world. The concept of a digital twin begins at the point of information collection in the real world and extends by integrating the information and physical worlds. Digital twin reflects the entity it represents in the real world obtained from the full use of history data, physical models, and the intricate process of simulation existing in the virtual space. With the rapid expansion of information economy and artificial intelligence, the approach of utilizing existing information for analyzing goods and services to generate focused recommendations is becoming more relevant.

Recommender systems provide information about advantages associated with the choice of an alternative course of action. The main objective is to generate personalized recommendations which lead consumers in a customized manner to suitable options in a large space of possible alternatives [6]. Traditional recommender systems provide all services available to consumers, while the next generation recommender systems are expected to be exhaustive and flexible enough to accommodate consumers current situation without compromising their personal information or privacy. In the energy sector, the idea of recommender systems have found relevance and for future energy system to thrive, consumer choice and participation has been identified as major player. One of the important ways of inducing sustainable behavioral change, promoting carbon-low technologies, and persuading consumers to save energy is through the use of recommendations. These ideas have been recently addressed in PEAKapp, IntelliSOURCE, RABIT, and Endesa projects that attempt to empower end-users to manage their own energy [7], [8], [9]. These solutions focus on utility's administrative users.

In light of these developments, this paper can be seen as a half-overview to innovative energy services based recommender systems. We recall the principal blocks, and explain how they can be used to generate more focused recommendations. Unlike the majority of existing approaches that are focused on utility-oriented solutions, we propose to rethink this concept and bring the consumer to the center of action by replacing clients by their digital twins. The proposed idea may provide energy saving options without the need to significantly alter the consumers lifestyle. This may be achieved by forecasting the consumer consumption profiles while simultaneously generating the recommendations required to optimize energy usage.

II. Innovative Energy Services

Providers of energy services are experiencing a paradigm shift on a global scale [1], [7]. With the availability of smart technological solutions, energy consumers are able to redefine their role to become more active players on the market. These services allow forward thinking utilities and digitally compliant consumers to make their claim in this rapidly advancing digital energy ecosystem. The prospect of energy services appears optimistic although most consumers still are uninterested, disengaged or unaware of the opportunities that are available to them. In most cases, the reason for such disengagement is that some consumers need more information or are afraid of making changes they believe may end up in complications. The success of innovative energy services, is fundamentally built on digitization that empowers consumers and creates new opportunities. In order for energy services to be acceptable on the market, consumers need to be notified of these services using abundant and reliable advices [7].

Research into persuasive technology reveals that the intervention of technological solutions can help consumers to achieve their pursuit for self-improvement. In the energy domain, consumers conservative behavior has been successfully influenced using tools such as social comparison, feedback, and goal settings. Traditional, expert advice based approach has also proven to be effective; however, it is hardly scalable to a larger number of users [10]. Recommender systems present better opportunity in advancing the energy saving domain for a wider audience. Such systems help consumers optimize their energy saving options and possibilities. Therefore, equipping energy services with recommender system may have much stronger effect on consumer energy behavior. In what follows, we discuss the common aspects of available solutions and highlight our idea. Figures 1 and 2 show the schematic and detailed overview of the proposed approach. It starts with the data collection related to energy behavior of a consumer and ends with targeted recommendations.

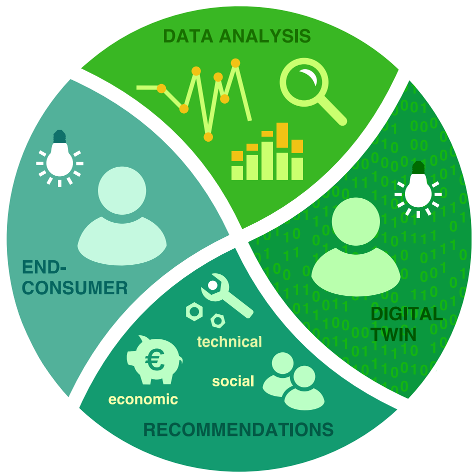

Fig. 1. Overall scheme of the presented consumer-oriented framework for recommendation of innovative energy services. Approach includes four main elements: end-consumer, (meta)data analysis, digital twinning, targeted recommendations.

III. Data and Metadata Analysis

Since the data cannot be used for either forecast or recommendation system in its raw form, it is therefore important to understand the key variables that affect and influence energy forecast. Efforts are therefore committed into preprocessing data to extract relevant features such as temperature, time, geographical location, social behavior, etc.

A. Social Media Support Feature

Using social media tools, campaigns on means of reducing energy consumption and energy awareness issues can be provided in a unique way. Social media application to energy behavior change aims to encourage energy saving behaviors via digital platforms, where consumers can collaborate in such a way that allows them to build a collective approach to efficient energy use. For example, Facebook and Twitter activities of consumers were analyzed and common energy objective is set, while consumers attempt to meet this objective [11]. In order to achieve an effective energy goal, social comparison is used to motivate consumers. Some applicable features are:

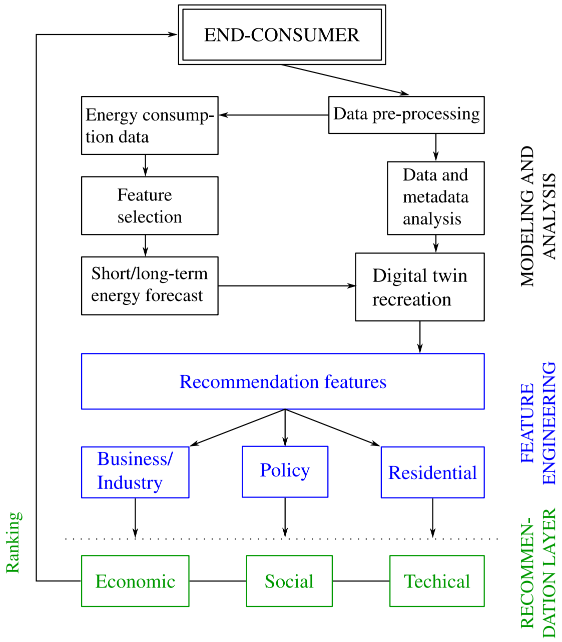

Fig. 2. Detailed scheme of the proposed framework with different layers.

- Neighbor comparison feature which allows consumer belonging to a given social media group to be compared and ranked against the average performance of other consumers in their social group.
- Additional feature of interest for recommendation includes likes, share, and lexicon features extracted from text messages.

By socializing the concept of energy, consumers are able to adjust their energy behavior based on social acceptable level. It is worthy of note that consumers intending to use social feature should have identical household type and reside in areas with similar local weather.

B. *Energy Forecast*

Load forecasting is a major component in energy management system of a household, and this could be categorized as short, medium or long term. The accurate prediction may significantly assist in understanding end-consumer behavior and habits. It shall get a special attention, since it is a major component of energy culture being complemented by other features from (meta)data analysis. Forecasting energy is affected by various factors such as seasonal effects, wind speed, precipitation, days of the week, random disturbances, customer mix, and time of the day. In particular, load forecast is usually done for short-term (one-day ahead) prediction, since longer period may not be reliant due to accumulated error. These challenges have led to the development of various price or electricity forecasting techniques [12].

Specifically, the accurate electricity consumption prediction is a hard problem due to complex relations between the participating factors and various local energy policies and requirements. The existing methods can be summarized as follows. Conventional methods include (non)linear regression, Box-Jenkins ARIMA and its variations [13]. Computational intelligence methods include neural network models [12], support vector machines, or their combinations [14].

C. *Digital Twinning*

In recent times, digitization is having tremendous effect in the way human live with increase in connection between products and their environment. Digital twin (DT) allows for an holistic and digital representation of consumers associated conditions and properties with an intention to analyze real-life behavior using data and models. A digital twin concept can be used to model the energy consumer with intent to address the lapses in consumer behavior and improve energy efficiency [15]. Previous attempts at simulating such technologies are used to achieve continuous interaction between digital environment and their physical twins. An example is the Model Order Reduction (MOR) which seamlessly reduces degree of freedom, maintain accuracy while reducing execution speed has been identified as a core technology for DT implementation. A major benefit associated with MOR is that it allows simulation models to be reused from early stage of development into the later phase of product life cycle. Again Functional Mock-up Interface is another modeling real-time DT implementation which has been deployed for industrial application. Digital twin design and implementation in the energy sector requires change in paradigm from the industry/utility and expert based to novel user or consumer based approach. The proposed consumer-oriented framework is derived from modeling methodology that integrates recommender system (scoring or ranking algorithm), historical and social media (meta)data analysis, short term/long term energy forecasting, machine learning models and visualization, to achieve the digital recreation of energy profile of consumers based on their energy behavior pattern, as detailed in Fig. 2. A major advantage associated with this approach is that, individual subset models are able to adaptively represent consumers and his environment to better represent the decision and provided recommendations.

IV. Recommendation Features/Tips

Tailoring energy conservation advice can be a daunting task as there is a need for clarity as which energy saving attribute or tip has effective influence on consumers decision. Consumers often struggle with the choice of appropriate measure for saving energy both in the household and industrial setting. Recommender systems hold the potential to adjust consumer pattern of interaction to user domain knowledge which in-turn increase the energy saving potential. Many efforts have been committed by most government to improve consumer energy conservation behavior through educational means and typically encouraging the use of renewable solutions considered to be more efficient [10]. To better address this problem, we present a framework that has been customized for various consumption categories supporting its associated independent features. The framework presents four major aspects for providing recommendations, which are the residential, policy, business, and industrial categories.

Business and industry: Features from this class use data that is unique or associated with the businesses such as the nature of machines, equipment, and devices used for production. In most cases users action and energy consumption profiles are processed by the framework to decide similarity recommendations, which are generated based on data obtained could be in form of heat and from electric drives.

Residential: Energy constitutes one of the major ingredients of modern living making it a prerequisite for business and households activities. Household energy consumption constitutes about 27% of total energy consumed in the entire EU. Important determinant features of household energy consumption include income level, size of household, geographical location, traditions, and cultural background. These features can be engineered to produce the digital twin of residents useful to better manage their energy consumption.

Policy: Adoption of innovative energy services will require policies among other things such as behavioral changes and adoption of new technologies. Policy implementation can result in many successes which may include institutionalizing of proper energy management schemes. Citizens are primarily responsible for the uptake and success of innovative solutions, and consumers across the EU will in the future have the opportunity to access reliable tools for energy price comparison. In addition, better regulatory framework creates an opportunity for the involvement of civil society in responding to price signals and the entire energy system. The dynamic behavior of energy consumer can be seen as a major area of discussion for energy policy makers. With a scale of one-third of the global energy consumption allocated to only residential consumers, governments all over the globe are seeking intelligent and novel approach to adapt energy saving prospects. It will be a daunting task to regulate the energy consumption of residential apartments without generating some level of distraction among residents. There is therefore need for reforms that identify the needs of energy systems and provide adequate incentives to support such agendas.

V. Ranking and Recommendations

Recommender systems have been traditionally studied in three main categories: content-based filtering, collaborative filtering, and hybrid approach. Collaborative filtering sought to find similarities between item description and user history, while content-based filtering recommends items based on consumer past experience. Recommender system helps user to make decision faster, acquire items that meet their needs, and reduce confusion in user decision making process. The main recommendation layers are defined as follows.

Social: The rapid development of social media networks and the techniques for social recommendations have profoundly influenced the way people live, making it a major driving force for encouraging energy saving behaviors. Social media sites are playing key role in mediated communication. About 73% of internet users are between the age 30 and 49, while 87% of online users are between 18 and 29 years [16]. The use of social media reminds other traditional mode of communication except that it allows exchange information on a wider basis with opportunity to consume social commentary alongside news content. This approach uses consumptive and expressive mode of consumer engagement. Both the social domain (interactions between user-to-user) and item domain (interactions between user-to-item) are unified by social recommendations.

Technical: Currently there are various policies aimed at increasing efficiency of the energy infrastructure, while other policies are attempting to make provision for retrofitting energy production with smart technologies. In this vein, consumers are equipped with the ability to monitor and manage their own pattern of energy consumption. Technical recommendations produce useful information that influence consumers behavior by encouraging them to take actions in conservation of energy by utilizing more efficient technologies.

Economic: Recommender systems have come mainstream in online purchasing environments, where they help consumers reduce costs while searching for products and making purchase decisions. Economic recommendation, depends on consumer behavior from economic perspective. Similarly, energy consumers are interested in recommendations that reduce their monthly energy bills. It is therefore seen that financial benefit is one of the main drivers for energy use reduction [17].

VI. Illustrative Example

Consider an illustrative example in which the first few steps of Fig. 2 are assumed to be performed and energy profile of a consumer alongside all the data is available. In what follows, we illustrate only the recommendation part. We have adopted cosine-similarity, among other alternatives such as Jaccard similarity, k-means algorithm, and Euclidean distance which lack meaningful semantic for ranking documents. As a first step, we implemented the recommendation section using Term Frequency and Inverse Document Frequency (TFIDF) [18] based on cosine similarities algorithm. Scoring was achieved using TFIDF for obtaining the cosine similarities score and was also used to determine the relevance and frequency of energy associated features. Consumption index was obtained as list of similarities scores which were sorted to obtain list of similarity scores. We adopted cosine similarities for ranking, since it does not consider the data size. A major advantage is that if two similar energy related features due to the size of information are far apart, the chance that they can be oriented closer to each other is much higher. Hence, recommendations/tips from the pool of available economic, social, and technology options may match the user needs much better then the traditional expert advice.

Table I shows the top seven recommendations sorted according to the score value computed from the energy forecast and analysis of the data for a given consumer. Figure 3 shows a potential effect from implementation of the respective recommendation. The example is intended to illustrate the idea of generating recommendations that target specifically the consumer needs without irrelevant suggestions from the third parties.

TABLE I
EXAMPLE OF TOP SEVEN RECOMMENDATIONS TO IMPROVE ENERGY EFFICIENCY

ID	Score	Recommendation	Layer
34	9.14	Install energy efficient LED bulbs in the lobby	Tech
18	8.42	Turn off light in the living room at bed time	Econ
13	8.32	Lower heat level at night by 0.1°C	Econ
38	8.16	Install heat pump	Tech
35	7.56	Install programmable thermostat	Tech
25	7.19	Encourage installation of renewable energy among social group	Soc
26	7.13	Like, share, and follow week energy top performer among social network	Soc

*Soc–social, Tech–technical, Econ–economic

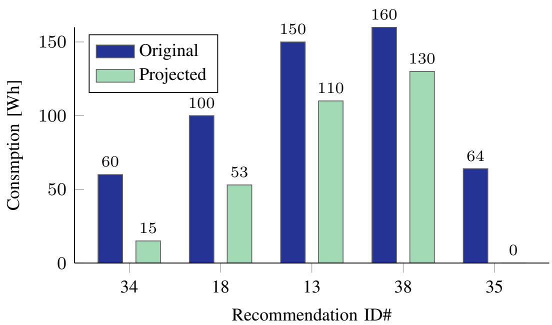

Fig. 3. Illustrative example of estimated improvement in daily consumption after implementing the proposed economic or technical recommendations.

VII. CONCLUSION

In this paper, we conceptualize the idea of innovative energy services oriented intelligent recommender system that allows households or consumers to receive smart and personalized recommendations based on their social preferences, location, family size, energy usage forecast, and other available (meta)data. Unlike the majority of utility-oriented solutions, we propose to bring the consumer to the center of action by replacing clients by their digital twins. Recent technological innovations make it possible to realize solutions that serve needs of regular people. The proposed idea provides energy saving options without the need to significantly alter the consumers lifestyle. This can be achieved by forecasting the consumer consumption profile while simultaneously generating the recommendations required for optimal energy usage.

Future work will be devoted to implementation of the (meta)data analysis tool and equipping other modules with more efficient algorithms. For example, the ranking algorithm can be further extended by multicriteria optimization heuristic algorithms that shall even better match recommendations. In addition, we plan to extend the recommendation pool by new layers and find the scenario that fits the regular consumer most.

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Appendix 2

II

A. Navon, R. Machlev, D. Carmon, A. E. Onile, J. Belikov, and Y. Levron. Effects of the COVID-19 pandemic on energy systems and electric power grids—a review of the challenges ahead. *Energies*, 14(4), 2021

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Article

Effects of the COVID-19 Pandemic on Energy Systems and Electric Power Grids—A Review of the Challenges Ahead

Aviad Navon [1], Ram Machlev [1,*], David Carmon [2], Abiodun Emmanuel Onile [3], Juri Belikov [3] and Yoash Levron [1]

[1] Technion—Israel Institute of Technology, The Andrew and Erna Viterbi Faculty of Electrical Engineering, Haifa 3200003, Israel; aviad.nav@gmail.com (A.N.); yoashl@ee.technion.ac.il (Y.L.)
[2] Israel Electric Corporation, Adi 1794000, Israel; david.carmon@iec.co.il
[3] The Department of Software Science, Tallinn University of Technology, Akadeemia tee 15a, 12618 Tallinn, Estonia; abiodun.onile@taltech.ee (A.E.O.); juri.belikov@taltech.ee (J.B.)
* Correspondence: ramm@campus.technion.ac.il

Abstract: The COVID-19 pandemic represents not just a global health crisis, but may signal the beginning of a new era of economic activity, the potential consequences of which we currently do not fully understand. In this context, the mid-to-long-range impacts of the pandemic on the energy sector have been studied extensively in the last few months. Despite these efforts, the pandemic still raises many open questions concerning the long-term operation and planning of power systems. For instance, how will the pandemic affect the integration of renewable energy sources? Should current power system expansion plans change in light of the COVID-19 pandemic? What new tools should be provided to support system operators during global health crises? It is the purpose of this paper to better understand the many aspects of these open questions by reviewing the relevant recent literature and by analyzing measured data. We point out the main challenges that the pandemic introduced by presenting patterns of electricity generation and demand, frequency deviations, and load forecasting. Moreover, we suggest directions for future research that may assist in coping with the mentioned challenges. We hope that this paper will trigger fruitful discussions and encourage further research on these important emerging topics.

Keywords: COVID-19; coronavirus; SARS-CoV-2; pandemic; health crisis; power system stability; renewable energy; energy market; energy policy; load forecasting

Citation: Navon, A.; Machlev, R.; Carmon, D.; Onile, A.E.; Belikov, J.; Levron, Y. Effects of the COVID-19 Pandemic on Energy Systems and Electric Power Grids—A Review of the Challenges Ahead. *Energies* **2021**, *14*, 1056. https://doi.org/10.3390/en14041056

Academic Editor: Evanthia A. Nanaki
Received: 20 December 2020
Accepted: 10 February 2021
Published: 17 February 2021

1. Introduction

On 30 January 2020, the World Health Organization declared the 2019 Coronavirus disease (COVID-19) to be a public health emergency of international concern [1]. The energy industry as a whole reacted very quickly and effectively to the pandemic. There was a clear understanding that delivering reliable electric power is an essential service, and that interruptions would have huge impacts that should be avoided at all costs [2,3].

The COVID-19 pandemic represents not just a global health crisis, but may signal the beginning of a new era of economic activity, the consequences of which we currently do not fully understand. In this light, the mid-to-long-range impacts of the pandemic on the energy sector have been studied extensively in the last few months. As any complex phenomenon, the COVID-19 pandemic may be studied using bottom-up synthesis, in which global trends are studied by observing local behavior, or using top-down analysis, in which trends are explored based on fundamental principles. Many examples for both of these approaches can be found in the recent literature. The bottom-up research approach has been implemented by studying the effects of the pandemic on power systems in several countries, such as the United States [4], China [5], Italy [6], Spain [7], Brazil [8], Canada [9], India [10], Sweden [11], Israel, Estonia, and Finland [12]. One clear trend emerging from these works is the effects of the pandemic on energy consumption patterns and peak demand, mostly due to the preventative measures taken by governments [13]. As part of this trend, many countries reported a significant reduction in electricity consumption in both the commercial and industrial sectors [14], which introduced numerous challenges to electric utilities and system operators [2,3]. Some of the challenges are a direct result of the irregular consumption patterns, e.g., high voltage levels and inaccurate load forecasting, whereas some of them are the indirect result of an effectively higher share of renewable energy generation, e.g., high ramp rates and fluctuations in frequency. In addition to the bottom-up approach, several top-down research efforts include new forecasting methods [15], long-term business impacts [2], the general effects of fast economic transitions [11,16,17], possible uses of machine-learning technologies [18], and the challenges related to the changing energy mix [2,12,16,19]. All the works mentioned above, as well as other works related to the impacts of the COVID-19 on energy systems and markets, are summarized in Table 1. The table presents the main focus of each work, as well as the geographical region of the study and the challenges discussed. As can be seen, the recent literature studies a wide variety of topics, including system operation, system planning, energy policy, energy markets, and additional sub-topics. Moreover, the number of papers that review each topic is more or less the same, and so the challenges are evenly represented. The references in Table 1 are presented in Table 2 according to their geographical scope. The table shows that currently most of the works focus on North America, Europe, and Asia.

Despite these ongoing research efforts, the pandemic still raises many open questions concerning the long-range operation and planning of power systems. For instance, how will the pandemic affect the global transition to a low-carbon economy, and, in particular, the integration of renewable energy sources? What will be the consequences for frequency stability? Should current power system expansion plans change in light of the COVID-19 pandemic? What new tools should be provided to support system operators during global health crises? The purpose of this paper is to better understand the many aspects of these open questions by reviewing the relevant recent literature and by analyzing measured data. To this end, we used the Scopus and IEEE Xplore databases and focused on papers that study the effects of the COVID-19 pandemic on electric power grids. The main keywords we used are detailed in Table 3. The search was also restricted to the fields title, abstract, and keywords. In addition, to complement data and ideas from the literature and to demonstrate some of the discussed challenges, we study measured data from both the Israeli power system operator and the European ENTSO-E Transparency Platform [20] and present meaningful patterns of electricity generation and demand, frequency deviations, and load forecasting. The latter was done in cooperation with the Israeli TSO. We hope that this paper will trigger fruitful discussions and encourage further research on these important emerging topics.

The paper continues as follows. Section 2 discusses the effects of the pandemic on energy consumption and renewable share, Section 3 discusses power system planning in light of global pandemics, Section 4 discusses decision support tools for system operators during pandemics, and Section 5 concludes the paper.

Table 1. Summary of works focusing on the impacts of COVID-19 on energy systems and markets.

Ref.	Work Focus	Study Region	Challenges
[4]	electricity demand and supply	USA: New York, California, and Florida	system operation, demand and demand ramp rate, load forecasting
[21]	energy sovereignty	regions in the USA and Canada	energy policies
[22]	energy use and home energy management	New York, USA	peak demand and demand ramp rate, energy market/prices
[23]	energy security	regions in the USA	energy policies
[24]	bulk power systems market operation	New York, USA	energy market/prices,load forecasting, energy policies
[25]	electric grid operation	regions in the USA and Europe	system operation challenges, system maintenance, peak demand and demand ramp rate, stability issue
[15]	load forecasting using mobility	regions in the USA and Europe	load forecasting, peak demand and demand ramp rate
[9]	electricity demand trend	Ontario, Canada	peak demand and demand ramp rate, load forecasting, energy market/prices
[26]	power system operation	Saskatchewan, Canada	system operators, load forecasting, stability
[8]	electricity load changes - statistical analysis	Brazil	peak demand and demand ramp rate, load forecasting, energy market
[27]	household energy use	China	energy market/prices, energy policies
[5]	electricity demand, economy and climate	China	system operators, peak demand and demand ramp rate, energy market/prices
[28]	the impact of the lockdown on power generation and load	China	system maintenance, energy market
[29]	photo-voltaic industry's grid parity	China	photo-voltaic forecasting, market/prices, energy policies
[12]	operation of small power grids	Israel, Estonia and Finland	system operators, system maintenance, voltage violation, peak demand and demand ramp rate, stability
[6]	electricity industry and bulk power system	Italy	energy market/prices, voltage violation
[30]	electricity market with large renewables	Italy	peak demand and demand ramp rate, energy market/prices
[31]	electricity consumption	regions in Europe	peak demand and demand ramp rate, system maintenance
[11]	sustainable electricity and mobility	Finland and Sweden	energy market/prices, energy policies, expansion of power system
[32]	people's behavior and residential energy sector sustainability	Kragujevac, Republic of Serbia	energy market/prices
[7]	electricity demand during pandemic	Spain	peak demand and demand ramp rate, energy market/prices, energy policies
[33]	immediate Impacts on the power sector	Europe	peak demand and demand ramp rate, energy market/prices, energy policies, system operators
[34]	electricity distribution system	India	system operators, voltage violation, stability, energy market/prices
[10]	energy consumption	India	energy policies
[35]	power sector operation	India	system operators, voltage violation, peak demand and demand ramp rate
[19]	energy industry	African continent	energy policies, expansion of power systems
[36]	energy access	African continent	energy policies, expansion of power systems
[37]	impacts caused by the falling consumption and demand in the electricity sector.	South Africa	peak demand, energy market
[3]	electricity demand and power system operation	USA, China, Italy, Japan, UK and Brazil	system operators, system maintenance, voltage violation, peak demand and demand ramp rate, energy market/prices
[18]	energy and AI technologies	USA, China, Germany and India	stability, load forecasting, energy market/prices
[2]	electricity industry	worldwide	system operators, voltage violation, load forecasting, energy market/prices
[16]	renewable energy	worldwide	energy policies
[38]	plastic waste, energy and environment	worldwide	energy market/prices, energy policies
[39]	energy demand and consumption	worldwide	peak demand and demand ramp rate, energy market/prices, energy policies

Table 2. Works sorted by continent and country.

Continent	References	Countries
North America	[3,4,9,15,18,21–26,39]	USA, Canada
South America	[3,8]	Brazil
Europe	[3,6,7,11,12,18,30,32,33,39]	Italy, France, Germany, Spain
Asia	[3,5,10,18,27–29,34,35,39]	China, India, Japan
Africa	[19,36,37,39]	South Africa
Australia	[40]	

Table 3. Search expressions that were used in the literature review. Note that the asterisk is used as a wild-card, allowing the search-engine to capture multiple variations of a word.

Primary Expression	Secondary Expression
	"(power OR energy OR electricity) AND (consumption OR demand)"
	"power system operator * OR transmission system operator *"
"COVID-19 OR coronavirus"	"energy market OR energy price * OR electricity price *"
	"(voltage OR frequency) AND (violation OR regulation OR deviation)"
	"load forecast* OR energy forecast *"

2. Effects of the Pandemic on Integration of Renewable Energy Sources

The reduced electricity consumption observed during the pandemic is mainly the result of government measures against the virus spread. In general, when policies to mitigate the pandemic became more severe, the consumption of electricity decreased. Two examples are shown in Figure 1 and Table 4. Figure 1 shows an example of the total daily average demand [MW] in France and Spain in 2018–2020. As can be seen in the figure, the demand in 2020 was considerably lower than in previous years. Table 4 presents the total energy demand and the maximum power demand in Israel during the nine–six weeks before, during and after the first lockdown (March–May 2020) and three weeks before and during the second lockdown (September–October 2020). The table shows that during the first and second lockdowns in Israel there was a decrease in both the energy and the maximum power demand and that as measurements got more severe during both lockdowns, demand further decreased. Moreover, we may clearly see that the measured metrics returned to their normal values as before the lockdown, indicating that the system recovered once governmental measures were relaxed. One direct result of the reduced consumption is an increased relative share of renewable sources in the energy mix. A possible explanation for this effect is that renewable sources are often prioritized over conventional power plants, and as a result their relative share increases when the consumption is low [12]. These phenomena can be seen in Figure 2, which presents the relative share of renewable energy in Israel in each of its lockdowns during 2020. As can be seen, the share of renewable energy increased during all three lockdowns. An exception to this trend is the third lockdown, in which the renewable share decreased towards its end, probably because it occurred during cloudy weather and was also lighter than the previous lockdowns. On the other hand, the first lockdown was the strictest and also occurred during the spring, when conditions for solar generation in Israel are optimal, thus the share of renewable energy was the highest. In fact, during this lockdown the renewable energy share reached new record highs. This is demonstrated in Figure 3, which presents the maximal share of renewable energy before and during the first lockdown. Before the pandemic the maximum share of renewable energy was 21.9%, but on 5 April the solar share reached 27% of the total generation, which was the maximum share of renewable energy ever measured in Israel. This record was broken again on 15 April, in which the solar share reached 29%. A similar effect was observed in many different countries [2,3,6,30], so a high share of renewable energy during the pandemic may be considered a global trend.

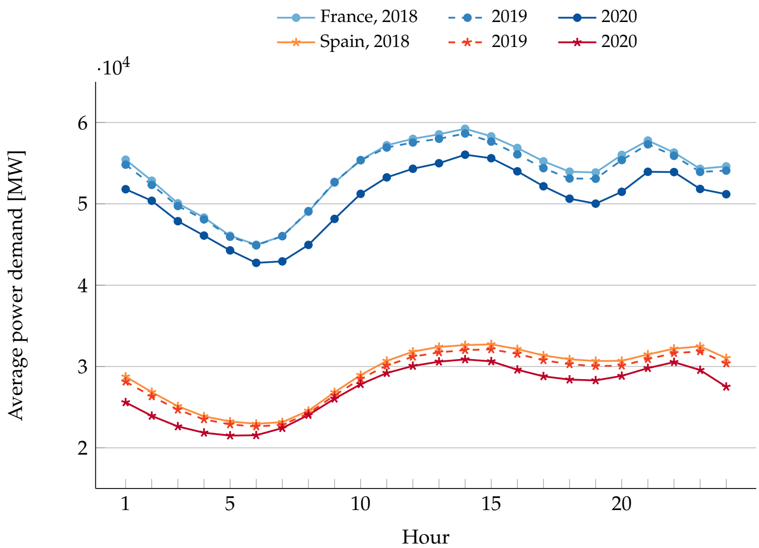

Figure 1. Comparison of the total daily average demand [MW] for 2018, 2019, and 2020 in France and Spain.

Table 4. Total energy demand [MWh] and maximum power demand [MW] before/during/after the COVID-19 lockdowns in Israel, 2020.

Week	Total Energy Demand [MWh]	Maximum Power Demand [MW]
02–08/03 (before 1st lockdown)	1,253,098	9166
23–29/03 (during 1st lockdown)	1,132,269	8494
30/03–05/04 (during 1st lockdown)	1,079,406	7946
27/04–03/05 (during 1st lockdown)	1,035,383	7294
04/05–10/05 (end of the 1st lockdown)	1,093,062	7559
11/05–17/05 (after 1st lockdown)	1,293,681	9232
14/09–20/09 (before 2nd lockdown)	1,744,541	12,725
21/09–27/09(during 2nd lockdown)	1,532,869	11,051
28/09–4/10 (during 2nd lockdown)	1,468,051	10,627

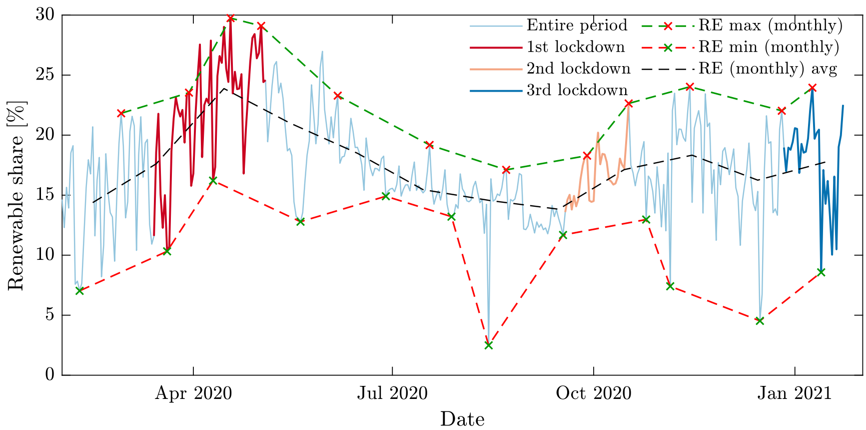

Figure 2. Renewable energy (RE) share (mainly solar) in Israel from 1 February 2020 to 23 January 2021.

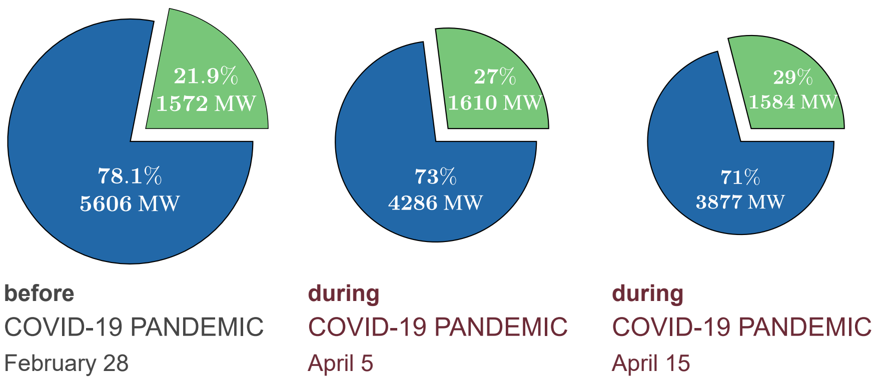

Figure 3. Maximum share of renewable energy in Israel before and during the first lockdown (2020), as a fraction of total generation.

In this context, how will the COVID-19 pandemic, and maybe other future pandemics, affect the integration of renewable energy sources in the long-term? A unique idea that may shed light on this question is the one of "economic shocks" [11,16,19,36]. According to this idea, if the integration of renewable sources can be described as a dynamic system operating on time-scales of years, then several months of low consumption may be viewed as a negative impulse signal (a shock), which causes reactions and counter-reactions that evolve in a closed feedback loop. In other words, the dynamic system describing the long-term integration of renewable sources is responding to an "economic shock"—an impulse signal that models a period of low energy consumption. An illustrative example is shown in Figure 4. In this model, $e(t)$ is the total energy demand; $c(t)$ is the cost of energy; $r(t)$ is the energy supply from renewable sources; $f(t)$ is the energy supply from fossil fuels; and $g(t)$, $h_r(t)$, and $h_f(t)$ are linear and time-invariant systems that links these signals to each other.

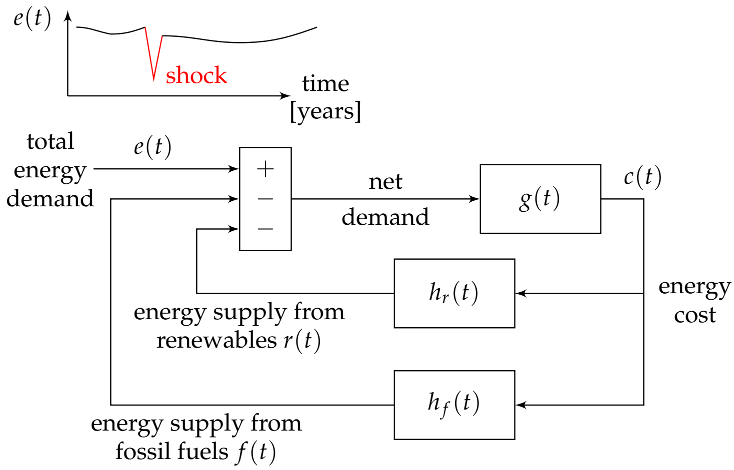

Figure 4. An illustrative feedback system describing the effects of "economic shocks": periods of low consumption are modeled as negative impulse signals, which cause reactions and counter-reactions that evolve in a closed feedback loop.

Here are two intuitions for dynamic interactions that may be triggered by such shocks. On one hand, economic shocks may *slow down* the integration of renewable sources, simply because weaker economies cannot allocate enough resources to sustain such development [36]. More specifically, the COVID-19 pandemic has already undermined renewable energy policies, which are under question even at normal times [16], thus delaying the deployment of renewable energy systems. On the other hand, it is also possible that the pandemic will eventually help *promote* the long-term integration of renewable energy sources, due to its negative effect on fossil fuel prices. During the pandemic, less fossil fuels have been used, which led to variations in these fuels prices (an "economic shock"). As fossil fuels production require large-scale investments in infrastructure, and such investments are questionable in periods of uncertainty, the pandemic may eventually trigger a domino effect (feedback) that may eventually enhance the integration of renewable energy sources [16].

Which of these two opposing trends will eventually prove to be more dominant? Suppose that we will see a series of economic shocks, being pandemic- or climate change-related, will they increase or decrease the use of renewable energy sources? What policies can be implemented now to support continuing integration of such sources, in spite of future economic shocks? While at the present time we simply do not know the answers, perhaps a clever dynamic modeling may shed new light on this complex problem.

Another result of the pandemic is that it provides a glance into a renewable-rich future, because, as discussed above, exceptionally low consumption leads to high share of renewable sources. An interesting question is therefore what can we learn from these periods of low consumption about renewable-rich power systems? Perhaps a few clues can be obtained by inspecting fluctuations in wholesale energy market prices, as they reflect in the recent literature. One recent work [2] shows that during lockdowns prices in Europe decreased dramatically, to less than half of the average price during the same period in previous years [2], and similar effects were reported in the U.S. [3] and India [34]. In addition, the authors of [6] study the impact of the pandemic on Italy's electricity consumption, wholesale electricity market, and ancillary services, concluding that while the Italian power system can run conveniently with a high share of renewable energy, the required ancillary services have a significant cost. The work in [30] supports this view, and shows that the lockdown in Italy resulted in a 103% increment in the cost of re-dispatch, when compared to the same period in previous years. The reason in this case is almost certainly the reduced consumption and the increased share of renewables.

Are these effects transitional in nature, or do they reflect real problems associated with renewable energy integration on a large-scale? As above, while currently we do not know the answer, perhaps clever dynamic modeling of energy-related economic processes can prove to be a viable research tool.

Last in this section, but not least, are problems that relate to frequency stability. In times of low consumption, or when renewable energy generation is high, fewer conventional power plants are operated, which leads to less spinning reserve and lower rotational inertia [41]. As a result, the frequency becomes less stable, and may deviate sharply following a loss of a generation unit, a fault, or a fast change in renewable energy production. The COVID-19 pandemic, again serving here as a large-scale experiment in renewable-rich power systems, demonstrated the severity of these effects. As an example, the effects of the pandemic on the frequency of the Israeli grid are summarized in Table 5. The table presents the number of seconds in which the frequency deviated from its nominal value during each week, for six weeks in March, April, and May, 2020. During all weeks reported the average temperature and cloudiness were similar, to mitigate the effects of varying weather conditions. In the table, frequency deviations are divided to higher and lower than 100 mHz or 200 mHz. The main conclusion from the data is that the overall duration of high frequency deviations increased during the lockdown and decreased back to normal values when the lockdown was over. This can be explained by the decrease in consumption, which raised the relative share of solar generation in Israel, as can be seen in Figures 2 and 3, and led to reduced rotational inertia. There is good reason to believe that such effects are global, so data recorded during the pandemic can be used as a research tool to better understand the frequency stability of future renewable-rich systems.

Table 5. Duration [in sec] of frequency deviations [in Hz] before and during the COVID-19 first lockdown in Israel, March–May 2020.

Week	<49.8	$[49.8, 49.9)$	$(50.1, 50.2]$	>50.2
02–08/03 (before 1st lockdown)	0	801	2195	32
23–29/03 (during 1st lockdown)	20	1612	2903	13
30/03–05/04 (during 1st lockdown)	128	4245	3716	667
27/04–03/05 (during 1st lockdown)	24	580	1805	22
04/05–10/05 (end of the 1st lockdown)	7	810	871	0
11/05–17/05 (after 1st lockdown)	7	57	1547	0

3. Expansion of Power Systems in Light of the COVID-19 Pandemic

Should the expansion plans of power systems consider the case of severe future pandemics? One reason to think so is the effects of pandemics on load distribution, following the demographic and economical changes they cause. Little evidence for such effects was provided by the COVID-19 pandemic in 2020, as reported in several recent works. During the pandemic people spend more time at home due to social distancing, which generally leads to larger load in the private sector [31]. Nevertheless, in several large cities the load decreased, as people migrated from urban to rural areas [12,42]. Such migration is made possible due to the growing trend of working and studying from home, and can be explained as a way of seeking refuge from populated areas, or a mean to reduce the cost of living in such difficult economic times [43]. These changes, in addition to uncertain load predictions in the industrial and business sectors [12], lead not only to a reduction in the total load, but also to very different geographical distribution of the same load. In this light, should additional transmission lines be placed in rural areas that may become more populated? Should distribution networks be upgraded in domestic areas as more people work from home? Can current forecasting models still be used for scheduling quarterly and yearly maintenance programs? These concerns join many others, and make the power system expansion planning problem even more complex than it already is [44].

Another related question is that of planned interconnections between neighboring grids. As discussed above, periods of low consumption undermine the stability of power systems, as less conventional units are being operated. Because larger systems are more immune to single failures, and therefore tend to be more reliable overall, a natural conclusion is that pandemics provide an incentive to interconnect. In this context, should decisions about future interconnections take into account possible global health crises? Past experience shows that stability and reliability by themselves are often not important enough to justify interconnections. Some examples are Israel, Japan, and Texas, which are until this day an "electric island", despite being relatively small in both area and overall power consumption. Perhaps the risk of pandemics, accompanied by the future rise of renewable energies, will affect this line of thinking. An opposite example is Estonia, whose government recently decided to disconnect from the Russian electric grid in five years. A natural question is what will be the effect of a future pandemic on the Estonian grid and the surrounding Baltic countries after the disconnection.

4. Tools to Support System Operators during Global Health Crises

As discussed in [2], system operators worldwide reacted very well to the difficulties caused by the COVID-19 pandemic, and were able to stabilize the system and provide electric energy to all who need it, with very few interruptions. Nevertheless, it was a challenging operation and is expected to become more difficult as the share of renewable energy will increase. Assuming that we will see more acute pandemics in the future, is there a place to consider special decision support tools [18], which may help system operators in times of severe health crises?

Naturally, if such a tool is to be developed, the problem of load forecasting should be at the center of attention. Most load forecasting algorithms receive as inputs the time, weather conditions, and load history, but do not consider socioeconomic changes, and therefore could not operate well during the first lockdown of the COVID-19 pandemic. To emphasize this problem, Figures 5 and 6 present the average daily load forecasting error in Spain and France during 2016–2020. Figure 5 presents data between January 1st and December 31th, excluding March 15th to April 15th, which is the period of the first lockdown, whereas Figure 6 presents data from March 15th to April 15th. Both Spain and France were strongly impacted by the COVID-19 virus spread, and both governments started implementing containment measures in mid-March 2020. As can be seen in Figure 5, excluding the dates of the first lockdown, there was no significant change in the forecasting error when comparing 2020 to previous years. However, Figure 6 shows that in both countries the forecasting error during the lockdown was significantly larger in 2020 in comparison to the same dates in previous years, emphasizing the difficulty in predicting load profiles during health crises, or any other large-scale event that dramatically affects social behavior.

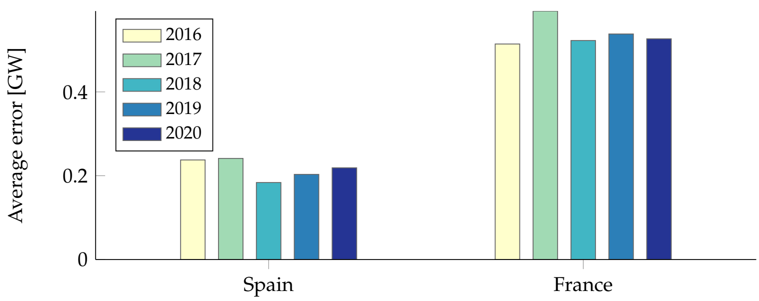

Figure 5. Average daily load forecasting error in Spain and France, between 1 January and 31 December, excluding 15 March to 15 April, 2016–2020.

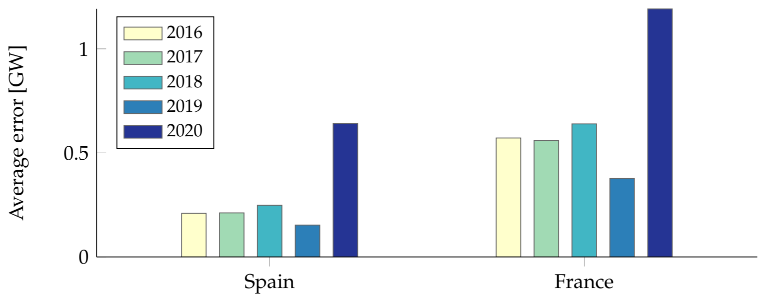

Figure 6. Average daily load forecasting error in Spain and France, between 15 March and 15 April, 2016–2020.

A different presentation of the same data can be seen in Figure 7, which shows the forecasting error in Spain and France between 15th March and 15th April in 2018–2020. The error is calculated as the difference between the daily average forecast and the actual load, and is presented in absolute values.

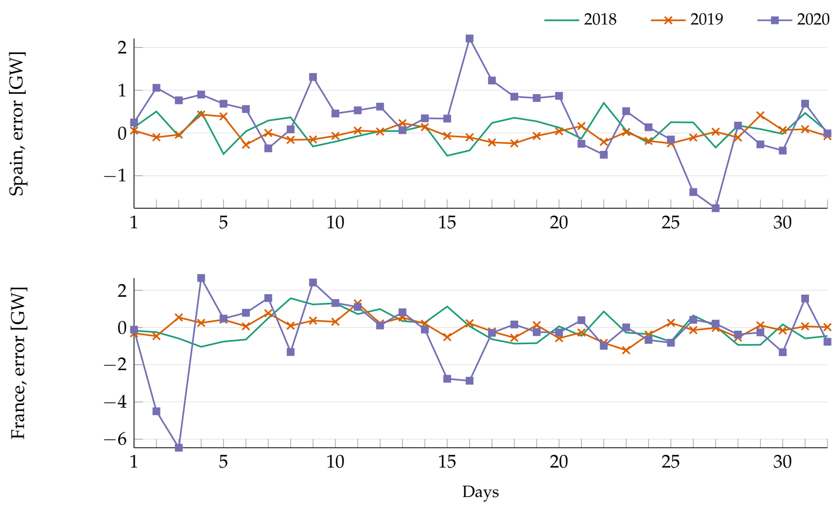

Figure 7. Load forecasting error in Spain and France between 15 March and 15 April in 2018–2020.

Another evidence for the same idea is shown in [5], where a neural network model is developed to analyze the impacts of COVID-19 on the electricity and petroleum demand in China. It is concluded that previous forecasting models that use historical trends are now inaccurate, due to the unpredictable human element embedded in global pandemics. On the other hand, it is important to note that the industry is well aware of this difficulty, and overall was able to provide first-order solutions which worked quite well [2]. For example, several utilities modified weekday forecasts to follow consumption patterns of weekends or holidays, thus providing a simple first-order solution to the problem above. Other utilities adjusted their forecasting models so that they would anticipate lower demand profiles, and asked for factories and commercial buildings to update in advance on any major changes in consumption. A more sophisticated solution has been proposed in [15], which suggests improving the forecasting by using mobility data to identify load changes caused by socioeconomic behaviors and governmental restrictions. It is most likely that this and other sophisticated forecasting methods will be needed to solve this important problem.

Another challenge to system operators which is caused by the reduced consumption is voltage deviations [2,12,34]. This is mostly due to shunt capacitance in transmission lines, that generate reactive power. When the overall consumption is low, this reactive power changes the power flow in the network, and may result in increased voltage amplitudes , i.e., the Ferranti effect. The issue of voltage stability was especially problematic in areas with factories and commercial buildings that were closed during the pandemic [3]. Usually, this problem is solved by operating synchronous machines in an under-excited mode, in which they absorb reactive power. However, when less conventional power plants are being used, this voltage control mechanism may be less effective. Another solution is to switch transmission lines on and off [2], as was done by utility companies in Asia and North America during the first few months of the pandemic. Can special-purpose algorithms help system operators decide on such actions in real-time? While such algorithms are probably not in high demand today, perhaps they will be needed during future periods of especially low consumption.

An additional challenge to system operators during periods of low consumption is increased ramp rates of conventional power (the infamous "duck curve"), which may lead to reduced reliability, poor resiliency, and non-optimal economic dispatch [12]. To demonstrate this, Figure 8 compares the overall demand and conventional generation in Israel during 24 hours in both March 4 and 29, 2020 (before and during the lockdown). As seen in the graph, the ramp rate of conventional generation between 15:00 and 20:00 on the 29th is significantly higher, with an increase of approximately 2900 MW, which was 34% of the peak conventional generation on that day, in comparison to an increase of about 2500 MW on the 4th, which was 27% of the peak conventional generation. Similar effects are reported in [6], which presents demand patterns in Italy during March 2020, and in [4], which examines the pandemic's impact on the demand in New York, California, and Florida using a simple linear regression model. Peak demand and ramp rate were identified in this last work as the main variables that contribute to the stress on the grid. It is possible that in the future special decision making tools may help system operators deal with these effects, perhaps by engaging fast-reacting units such as renewable sources or storage devices.

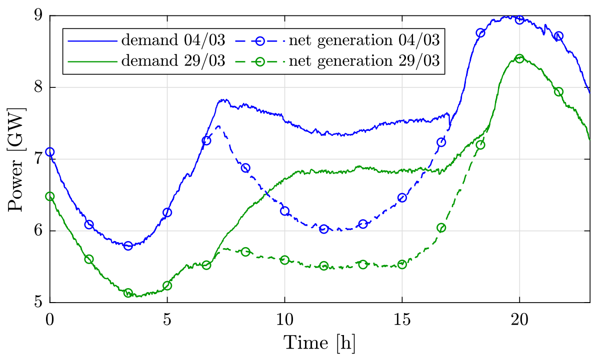

Figure 8. Comparison of the total demand and conventional generation in Israel during 24 h on two sunny days: 4 March and 29 March 2020.

5. Conclusions

Power systems have been going through a transitional change in the last few years, with the integration of new technologies such as electric vehicles, storage devices, and renewable energy sources. In the midst of this change, the COVID-19 pandemic triggered socioeconomic phenomena that led to very different patterns of energy consumption, and by doing so emphasized the most crucial problems of this global transition. The current paper focuses on three such problems: the effects of the pandemic on the integration of renewable sources, its possible effects on expansion planning problems, and the technical difficulties faced by system operators. The mentioned open questions concerning the long-term operation and planning of power systems under the effect of the pandemic are summarized in Table 6. A key question is how the pandemic will influence the global transition to a low-carbon economy and, in particular, the integration of renewable energy sources. This question has two aspects: one of policy, the other of economy. With regard to policy, the pandemic caused a decrease in consumption, which raised the relative share of renewable sources in the energy mix, and provided us a glance into a renewable rich future. Therefore, the question is how policy-makers will react to evidence from the field. On the one hand, the high share of renewables revealed to be challenging, as it led to low inertia, reduced frequency, voltage instability, "duck curve" effects, and fluctuating prices. On the other hand, although the renewable share increased, system operators worldwide were able to manage it without major failures. As for the economic aspect of this question, the pandemic damaged both the fossil fuel industry and the ability of many governments to continue supporting the renewable energy industry, and so it is currently unclear how these industries will recover. To understand the impact of the COVID-19 on renewables under different policy schemes, there is a need for a sophisticated dynamic model that will capture to relationship between energy demand, energy prices and generation of both fossil fuels and renewables. Another important question is how the pandemic affects current power system expansion plans. Evidence shows that the pandemic did not only cause a reduction in electricity load, but also a load shift from the industrial and commercial sectors to the private sector, and from large cities to peripheral settlements. Therefore, there is place for clever load forecasting models that will take into account changes in both social and demographic behavior. This may trigger and update current expansion plans, with accordance to the expected changes. Moreover, due to the many technical difficulties that electric grids experienced during the pandemic, there is a need to assess the vulnerability of small electric grids to global health crises and an increasing share of renewable energy. The last but not least major question we investigate in this paper is the need for decision supporting tools for system operators in times of abnormal consumption. We show that during lockdowns there was a significant increase in frequency deviations and load forecasting errors. Perhaps advanced models, for instance, machine learning-based algorithms, may assist system operators during crises. For example, novel solutions may use new sources of data, such as mobility data, national health status, and governmental restrictions, to forecast the expected demand in the short-term, and point out the optimal network topology or generation dispatch. A central idea in this work is that the pandemic is a large-scale socioeconomic phenomenon, and as such reveals new data that may help the community to better understand the power systems of tomorrow. The pandemic, with all its difficulties and problems, provided the power system community priceless data, which should be exploited for further research.

Table 6. Summary of open questions and challenges.

Category	Open Questions and Challenges
Renewable energy integration	✓ How will the pandemic affect the energy mix in the long-term, and specifically the integration of renewable energy sources? ✓ Suppose that we will see a series of economic shocks, be them pandemic or climate change-related, will they increase or decrease the use of renewable energy sources? ✓ What will be the consequences for frequency stability? ✓ What policies can be implemented now to support continuing integration of such sources, in spite of future economic shocks?
System expansion planning	✓ Should current power system expansion plans change in light of the COVID-19 pandemic? ✓ Should additional transmission lines be placed in rural areas that may become more populated? ✓ Should distribution networks be upgraded in domestic areas as more people work from home? ✓ Can current forecasting models still be used for scheduling quarterly and yearly maintenance programs? ✓ Should decisions about future interconnections take into account possible global health crises?
System operation	✓ Which new tools should be provided to support system operators during crises? ✓ Can special-purpose real-time algorithms help system operators decide on the optimal topology for voltage stability and the optimal generation unit dispatch for frequency regulation?

Author Contributions: All authors have worked on this manuscript together. All authors have read and agreed to the published version of the manuscript.

Funding: The work of Y. Levron was partly supported by Israel Science Foundation grant No. 1227/18. The work of A. E. Onile has been partially conducted in the project "ICT programme" which was supported by the European Union through the European Social Fund.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

COVID-19	Coronavirus disease 2019
ENTSO-E	European Network of Transmission System Operators for Electricity
SARS-CoV-2	Severe acute respiratory syndrome coronavirus 2
TSO	Transmission system operator

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Appendix 3

III

A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. A comparative study on graph-based ranking algorithms for consumer-oriented demand side management. In *Proceedings of 2021 IEEE Madrid PowerTech – 14th IEEE PowerTech*, pages 1–6, 2021

A Comparative Study on Graph-based Ranking Algorithms for Consumer-oriented Demand Side Management

Abiodun E. Onile, Juri Belikov
Department of Software Science
Tallinn University of Technology
Tallinn, Estonia
{abiodun.onile, juri.belikov}@taltech.ee

Eduard Petlenkov
Department of Computer Systems
Tallinn University of Technology
Tallinn, Estonia
eduard.petlenkov@taltech.ee

Yoash Levron
Faculty of Electrical Engineering
Technion—Israel Institute of Technology
Haifa, Israel
yoashl@technion.ac.il

2021 IEEE Madrid PowerTech | 978-1-6654-3597-0/21/$31.00 ©2021 IEEE | DOI: 10.1109/PowerTech46648.2021.9494752

***Abstract*—In the recent years, the impact of urban climate change and ever-expanding needs for electricity energy calls for urgent attention. Generally, electricity can be conserved by implementing efficiency models that handle effective utilization. To set and monitor energy conservation goals at consumer end, this study presents an innovative ranking approach as Demand Side Management technique for estimating the amount of energy used by consumers toward identifying potential savings. We further present comparative analysis of five unsupervised graph-based ranking techniques such as PageRank, TrustRank, Hyperlink-induced search, Markov chain, and Differential ranking algorithms for proffering suitable solution to energy conservation problems. The various ranking methods were evaluated in the context of consumer-oriented energy services.**

***Index Terms*—Electricity, graph-based ranking, consumer-oriented demand side management, energy conservation, innovative energy services**

I. Introduction

In view of increasing energy consumption and consequent environmental concerns, attention has been drawn to consumers to effect energy efficiency measures. Challenges however occur due to deficiencies on the side of consumers to effect measures. In most cases, consumers are less cautious about energy savings and there is limited basis for assessing consumers' energy behaviors [1]. In addition, consumers lack in technical aptness, economic and time requirements, which are necessary for wholesome evaluation of energy efficiency (measures). For example, energy consumer behavior is abstract (W and kWh are abstract units) and therefore possess low personal relevance to majority of consumers and as such proves difficulties to understand by end consumers [2]. Previous attempts by energy service contactors aiming at providing consumers with energy saving awareness (efficiency reports) are less scalable and results are error prone [3].

The work of A. E. Onile and E. Petlenkov was partly supported by the Estonian Research Council grant PRG658. The work of Y. Levron was partly supported by Israel Science Foundation grant No. 1227/18.

978-1-6654-3597-0/21/$31.00 ©2021 IEEE

A possible solution is to introduce innovative and consumer-oriented methods for comparison of consumers' energy profiles to reveal ranks while providing actionable suggestions to improve their ranks and influence reduction in consumption [1]. Graph-based ranking models have successfully been applied as traditional means for analyzing the world-wide web's link structure and social networks [4]. These include the Google's PageRank [5] and Hyperlink-induced search (HITS) algorithms [6]. Similarly, this approach can be applied to consumer energy graph extraction leading to a novel ranking approach where information obtained from consumer energy consumption can be used to make a local ranking decision. Ranking prediction of consumer energy profiles can help plan for energy loss mitigation based on adjusting consumer energy behavior [7]. The strength of the identified ranking approach relies keenly on their ability for processing ambiguity and vagueness associated with consumer judgments thereby representing linguistic terms with quantifiable numbers [2].

Several studies have revealed that feedback has potentials for stimulating consumers underlying believe towards adopting energy saving attitudes [8], [9]. Work [10] presented webpage ranking approach using discrete-time Markov Chain (MC) for cooperative edge computing networks' energy saving model. Work [11] introduced a smart energy ranking model for analyzing user behavior on webpage (saving web energy). Majority of these works are centered solely on web applications. At the same time, none of these have attempted direct application to electricity consumption signal/profiles. Study [12] presents approach for ranking electric feedback in homes towards effecting behavioral change in consumption.

Similarly, a consumer-oriented Demand Side Management (DSM) approach has attracted a lot of attention. Work [13] presented a study on citizen-oriented energy management platform. A major problem is the need for high computing capacity to handle the influx of information (large volume of data) which translates into energy consumption. A consumer-oriented ranking framework based on advance warning tool for electric power payments has been presented in [14]. The proposed neural network and fuzzy probability model use credit scoring approach to provide advanced warning of potential electrical fee risks. An energy aware ranking in service-oriented computing has been published in [15]. The proposed model targets the energy consumption profiles of services towards reduction in technological energy waste. These solutions however are not directly effected on consumers' energy signal, creating needs for additional/excessive processing demands.

To the best of the authors' knowledge, there are limited studies discussing aggregation of graph-based ranking models for analyzing consumer-oriented energy consumption profiles. Thus, we propose here a novel approach for advancing functionality of existing models. The aim of this study is to analyze various ranking models: PageRank, TrustRank, Hyperlink-induced search (HITS), MC, and Diffusion ranking to determine the degree to which individual consumer energy consumption is influenced by behavioral pattern. To this end, we present a novel graph-based signal processing approach for modeling consumers behavioral pattern from time variant energy signals, showing the competitive potentials of various graph-based ranking models for scoring consumer energy performance towards enforcing DSM measures.

II. Background of Study

Here, we briefly recall the theoretical basis for modeling and scoring consumer electricity behavior towards effecting energy management. Ranking algorithms have been extensively researched area of information retriever. Key elements of energy consumption data can be accurately measured using graph based ranking algorithm such as PageRank, TrustRank, HITS, MC, and Diffusion ranking model.

A. PageRank

PageRank intuitively models the behavior of consumers. It captures intrinsic features in data based on feature selection of elements that strongly correlate with most of the features appearing in a data set. The algorithm iteratively determines scores associated with each vertices as an integration of the entire weighted scores of connected vertices. This can be defined as [16]

$$PR(V_i) = (1-d) + d\sum_{i=1}^{N} \frac{PR(v_i)}{N(v_i)}, \tag{1}$$

where d is the damping factor, $PR(v_i)$ is the currently ranked consumption profile, and N is the total number of nodes.

B. TrustRank

TrustRank was originally developed in [17] to manage spam on the web. The basis for TrustRank is that good sites (edges) scarcely point to spam site thus increasing people trust for these sites. Such trust could be propagated via the web's link structure. The algorithm selects a set of trustworthy sites to build a set of seed trust, with each site assigned with initial trust scores. These initial trust scores are propagated to outgoing sites using PageRank model. This model is defined as

$$t^* = \alpha T t^* + d(1 - \alpha), \tag{2}$$

where t^* is the TrustRank scores, α is the decay factor, T_r denotes the transition matrix, and d is the normalized vector for the seed set.

C. Markov Chain Model

This model is able to provide capacity for a holistic viewpoint for comparing rank candidates. MC ranking models the sequential behaviors of consumer and predicts their next actions from a learned transition graph of their previous (last) action. Transition matrix of an MC model gives an estimation of consumers' probability of belonging to the given energy consumption profile. The model can be described as [18]

$$MC = \frac{1}{N-1}\sum_{j=1}^{N} P_{i>j}, \quad P_{i>j} = \phi\left(\frac{\hat{\mu_i} - \hat{\mu_j}}{\hat{\sigma_{ij}}}\right), \tag{3}$$

where i, j represent the source and destination nodes, respectively, $P_{i>j}$ is the probability that node i returns better scores than j, N is the number of nodes, and ϕ represents cumulative density function obtained from standard normal distribution. $\hat{\sigma_{ij}}$ is the estimated standard error of estimated difference $\hat{\mu_i} - \hat{\mu_j}$ between two ranked profiles.

D. HITS Algorithm

HITS (Hyperlink-Induced Topic Search) model is an Eigenvector-based ranking approach for ranking the webpages [6]. This model allocates two scores to each node namely hub (centrality) score (5) and authority score (4). Hub scores are usually large for nodes that points to large number of authority nodes. A mutual reinforcement relationship between two scores is further described in

$$HITS_A(v_i) = \sum_{v_j \in P_{to}} HITS_H(v_j) \tag{4}$$

and

$$HITS_H(v_i) = \sum_{v_j \in P_{from}} HITS_A(v_j), \tag{5}$$

where P_{to} is all pages which link to page v_i, P_{from} is all pages which page v_i links to, and v_i and v_j represent the source and destination nodes, respectively

E. Diffusion Ranking Model

This can be described as heat (diffusion) equation [19]

$$\frac{\mathrm{d}u_i}{\mathrm{d}t} = c\sum_{j=1}^{n} A_{ij}\left(u_j - u_i\right), \tag{6}$$

where c represents the rate of diffusion between two connected pair of nodes. The scoring mechanism is modeled on the basis of constant value of c, termed homogeneous diffusion. The transition matrix A_{ij} encodes the graph connectivity from the source node i to destination node j over a time period $\mathrm{d}t$.

F. Consumer Behavior Analysis

Understanding of consumers' daily routine constituting energy consumption behavior is crucial for successful DSM programs. Similarly, awareness creation (and education) is equally important as monetary factors in promoting DSM solutions [20]. As such, consumers' scoring supports behavioral control-switch, towards effecting energy reduction transition.

We approach this problem by describing consumer behavior using graph-based analysis. Consumer energy profile can be described as a time-varying information flow playing a crucial role in evolution of behavior graph topology (rise and fall of edges and nodes). A significantly studied problem relating network evolution is link prediction, which suggests links that will emerge in the future. Ranking can be achieved by analyzing/predicting the load dwell time thereby alerting consumers once a frequent load level (base, medium or peak) has been identified. Consumer or node transition behavior can be predicted using graph-based ranking models.

III. Methodology

This section demonstrates application of various graph-based ranking models for scoring end-consumer energy profiles. We consider various graph-based approaches to modeling consumer energy behavior while estimating performance based on comparative analysis. This proffer a simple yet powerful approach to effect DSM solution.

Time variant consumer energy signal can be discretized in levels [21] (low or baseline, medium, and high or peak) corresponding to the essential consumption behavioral pattern (see Fig. 1). This data was preprocessed into the required consumers' rating matrix format (transition matrix)

$$A_{ij} = \begin{array}{c c} \text{load-}C_r & \begin{array}{ccc} b & m & p \end{array} \\ \begin{array}{c} b \\ m \\ p \end{array} & \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{bmatrix} \end{array}, \tag{7}$$

where i, j represent the source and destination nodes, respectively. The rating matrix A_{ij} was developed based on transition between a group of criterial such that $C_r = \{A_j \mid j = 1, 2, 3\}$ represents the various discrete levels of energy profiles. Transition matrix represents the various discrete levels of energy profiles (base, medium or peak), e.g, as depicted in Fig. 1.

The transition matrix is used as input for computing the ranking scores of various consumers energy profiles using ranking models. The rating associated with a given active profile is predicted in the form of an actionable score. Data was analyzed using accuracy analysis to evaluate individual performance of the models. The developed methodology produces an open approach to obtaining comparative analysis of graph-based ranking models for energy consumption dataset.

The evaluation techniques (models) are further described as:

- *Statistical accuracy metrics*. This technique obtains a comparison between predicted and actual rating, using Kendall's-τ correlation.
- *Classification accuracy metrics*. This technique determines whether a scoring is good or not, based on the frequency of occurrence. For example, Kolmogorov–Smirnov test and F-measure belongs to this category.

Kendall's-τ correlation can be defined as [22]

$$\tau = 1 - \frac{2S(\pi, \sigma)}{N(N-1)}, \tag{8}$$

where π and σ represent the ranking order of consumption profiles from a given set, N is the number of items being ranked, $S(\pi, \sigma)$ is the minimum amount of adjacent transposition required to transition π to ρ.

Further, we evaluated various ranking methods using Average Precision (AP) which measures the average of precisions after obtaining relevant ranking of consumer profiles. AP can be computed as

$$AP = \frac{1}{N_{pos}} \sum_{j=1}^{N} P(j) \times \mathrm{rel}(j), \tag{9}$$

where AP is the average precision, N_{pos} is the number of positives and $P(j)$ is the precision at node j, $\mathrm{rel}(j)$ represents relevance function of the element i belonging to a given list.

In addition, we use the F-measure given by

$$F\text{-measure} = \frac{2\text{Precission} * \text{Recall}}{\text{Precission} + \text{Recall}}, \tag{10}$$

where

$$\text{Precission} = \frac{\text{Relevant scored items}}{\text{Total scored items}}, \tag{11}$$

and

$$\text{Recall} = \frac{\text{Relevant scored items}}{\text{Total relevant scored items}}. \tag{12}$$

To validate the results we further use Kolmogorov-Smirnov test defined as

$$D_n = \sup_x |F_n(x) - F(x)|, \tag{13}$$

where $\sup_x$ represents the supremum set of rank distances, $F(x)$ is the cumulative distribution function, x is an ordered observation of ranked profiles, and F_n is the empirical distribution of identical, but independent distribution.

IV. Numeric Results

To evaluate the performance of ranking models, we assessed the quality of score generated by individual scoring models using two different metrics (classification and statistical accuracy). Utility dataset was obtained comprising consumption profiles spanning seven days' duration (time stamps). For example, we computed transition between following load criteria (load scale reference) where we (discretized consumption profiles) decided that load in range $0 \leq b \leq 80$ Wh, $81 \leq m \leq 200$ Wh, and $p \geq 201$ Wh rank as either base b, medium m or peak p, respectively. In transition matrix A_{ij}, $a_{1,3}$ represents transition frequency (dwell time) from base to peak load. Similarly, $a_{1,1}$ is transition from base-to-base load.

Figure 2 visualizes the degree of τ linearity existing between inter-day ranking in the period under consideration (period

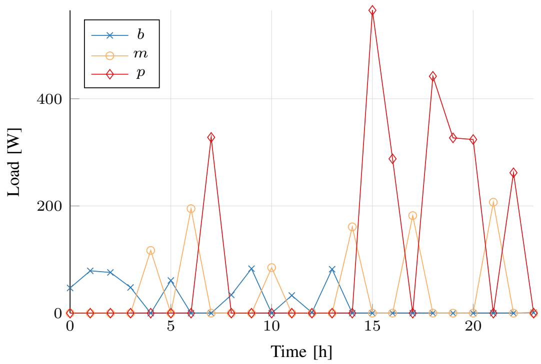

Fig. 1. Visualization of typical electricity daily consumption profile for peak p, medium m and baseline b load.

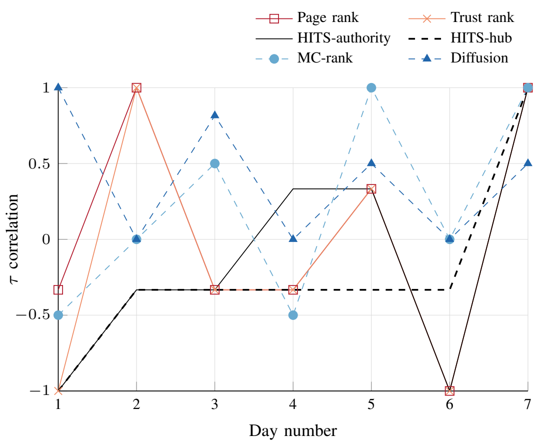

Fig. 2. Visualization of Kendall-τ rank correlation curve for inter-day rank distribution for seven day period.

Day1-Day7). The comparison yielded a τ correlation coefficient of 1 ($6 < \text{Day} \leq 7$) which signifies that majority of the ranking models converge on Day7.

We evaluated the performance of ranking models using (11 point) interpolated average precision (AP). This is computed by considering the area under the curve using the maximum observable precision matched with recall at each cut-off level $(0, 0.1, \ldots, 1)$. Table I describes the mean of precision score associated with relevance of rank outcome returned by the ranking models. PageRank and TrustRanks recorded the highest AP of about 91% relevance score. This result is closely followed by HITS and MC with about 82% and 83%, respectively.

Table II describes the measure of relevance of rank outcome. F-measure shows an increasing trend of rank accuracy from Day 1 to Day 7 (Ranging from about 18.7 to 92%), with PageRank and TrustRank recording 92% capacity for relevant ranking (on days 6 and 7). The least performance was recorded by Diffusion ranking which returns about 64% capacity for relevant ranking (on $6 < \text{Day} \leq 7$).

TABLE I
EVALUATION OF VARIOUS RANKING MODELS USING AVERAGE PRECISION METRIC

PageRank	TrustRank	HITS	MC-rank	Diffusion
0.912	0.912	0.8271	0.8227	0.7155

TABLE II
SUMMARY OF F-MEASURE BASED ANALYSIS FOR VARIOUS RANKING MODELS

	1	2	3	4	5	6	7
PageRank	0.1877	0.2905	0.4431	0.599	0.7263	0.8328	0.9225
TrustRank	0.1877	0.2905	0.4431	0.599	0.7263	0.8328	0.9225
HITS	0.2454	0.3667	0.5434	0.7183	0.7149	0.6736	0.764
MC-rank	0.1645	0.4445	0.6055	0.6887	0.7617	0.7525	0.8038
Diffusion	0.2534	0.4941	0.5606	0.6372	0.6129	0.6187	0.6431

Figure 3 describes the Precision-Recall curve (RUC-curve), for a side-by-side comparison of various rank models on similar consumption/test data. Precision-Recall (accuracy) analysis reveals that PageRank and TrustRank both show exceptional performance compared to other ranking models. MC-rank model outperforms in precision at low recall values (0.5) when compared to other models. However, similar comparison at higher values of recall (0.8 or 1) returns worse precision scores overall compared to PageRank and TrustRank. This result is indication that PageRank and TrustRank can help achieve better ranking of consumption profile.

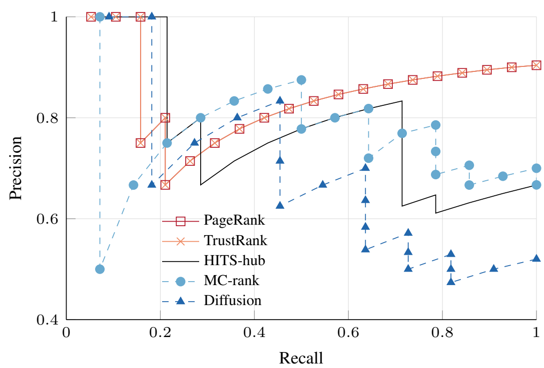

Fig. 3. Precision vs recall plot of ranking models.

Figure 4 describes the receiver operator characteristic (ROC) or true-positive rate (TPR) vs false positive rate (FPR). This curve describes trade-off between rank benefits (TPR) and cost (FPR). The best possible prediction can be associated with PageRank and TrustRank which return sensitivity result (100%) compared to other models at cost of 20% (low FPR). Following closely is MC-rank which recorded a sensitivity (TPR) of 85% at higher cost of 45%.

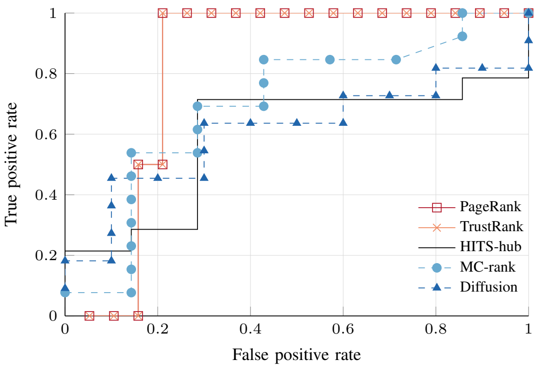

Fig. 4. Receiver operator characteristic (ROC): True positive rate vs false positive rate plot of ranking models.

Figure 5 shows the analysis of the models' suitability for effectively scoring consumers energy profiles using Kolmogorov-Smirnov index. For the period under consideration, PageRank and TrustRank returned about 78.9% capacity to separate these profiles, closely followed by HITS with 41%. This outcome corroborates results from previous analysis.

Furthermore, we explore the linearity between each ranking model using statistical evaluation metric (Kendal-τ correlation analysis) on the baseline data (Table III) and inter-day consumption profiles (Fig. 2). An ideal correlation score is considered to be 1. Table III compares how much each ranking score differs when evaluating the baseline data (reference point). PageRank, TrustRank, and HITS show a high inter-rank correlation of 1, while MC-rank returned moderate correlation of 0.82. This result shows the extent of similarity in terms of performance on the reference data.

TABLE III
SUMMARY OF KENDAL-τ CORRELATION ANALYSIS FOR VARIOUS RANKING MODELS

	PageRank	TrustRank	HITS	MC-rank	Diffusion
PageRank	1.0	1.0	1.0	0.816	0.0
TrustRank	1.0	1.0	1.0	0.816	0.0
HITS	1.0	1.0	1.0	0.816	0.0
MC-rank	0.816	1.0	0.816	1.0	−0.5
Diffusion	0.0	0.0	0.0	−0.5	1.0

Figure 6 compares the performance of various rank models in effectively scoring different load criteria (b, m, and p).

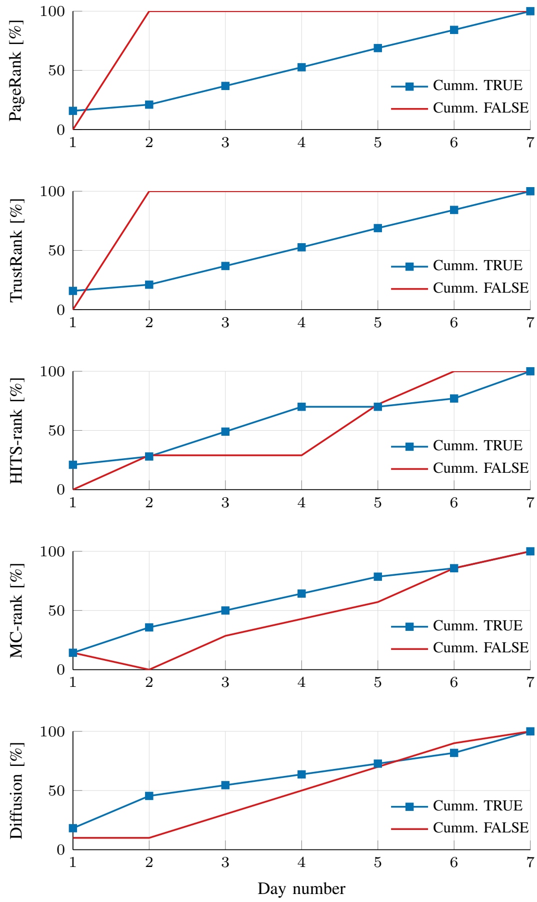

Fig. 5. Komolgorov-Smirnov index for comparative study of ranking models.

Study results revealed PageRank and TrustRank were unique in this regards. For example, PageRank and TrustRank both scored b, m, and p as 34, 33, and 33% respectively based on dwell time (for input see Figure 1). Intuitively, high PageRank scores for baseline b suggests the consumption profile (behavior) is efficient (within acceptable range) compared to m and p each with 33% scores. Similarly, HITS ranked b, m and p as 55, 22, and 22% respectively also indicating the relevance of baseline b profile. Such outcome over wide spectrum of consumption profile can significantly influence consumers' perspective towards maintaining optimal energy behavior.

To summarize, the results of experiments (classification accuracy) show dominant performance of PageRank and TrustRank. A possible reason for such outcome is that the two models are identical in all sense except TrustRank incorporates badness of nodes (spam). This makes TrustRank judgment

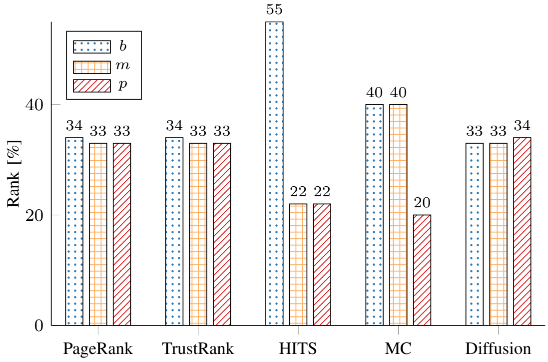

Fig. 6. Performance of various ranking models for scoring b, m, and p load profiles.

subjective and requires human evaluation to determine whether a node can be considered good or bad. PageRank on the other hand has no such knowledge about the quality of nodes. This feature has not been considered in our case, justifying the high degree of rank linearity between the two models. Similarly, PageRank and TrustRank showed exceptional performance in providing targeted feedbacks (scores) of consumer energy behavior towards effecting tailored DSM intervention.

V. Conclusion

A novel approach using comparative analysis for effective evaluation of graph-based ranking algorithms for consumer-oriented DSM solution has been investigated. Accuracy analysis revealed PageRank and TrustRank both show impressive results as optimal energy saving scoring measure. An advantage of proposed unsupervised graph-based method relates to less computational requirements. Additional significant benefit is that the study revealed the ability of ranking algorithms to effectively model consumer transition behavior towards effecting DSM solution. A possible limitation is that efforts in further quantizing energy consumption data may be required to extend the model's efficacy.

Although, we were able to examine several perspectives from this initial study, future research can be directed to the implementation of consumer-oriented graph-based ranking model suitable for electricity retail plans and comparison of outcomes to other non-intrusive load monitoring (e.g., NILM) approach. At the same time, we aim to focus on the development of consumer-centric personalized recommendation based on ranking outcomes in the future. Finally, efforts can be committed to cost-benefit analysis and testing the algorithms based on larger dataset to further validate the relevance of this approach.

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Appendix 4

IV

A. E. Onile, R. Machlev, E. Petlenkov, Y. Levron, and J. Belikov. Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. *Energy Reports*, 7:997–1015, 2021

Energy Reports 7 (2021) 997–1015

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Review article

Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review

Abiodun E. Onile [a], Ram Machlev [b], Eduard Petlenkov [c], Yoash Levron [b], Juri Belikov [a,*]

[a] Department of Software Science, Tallinn University of Technology, Akadeemia tee 15a, 12618 Tallinn, Estonia
[b] The Andrew and Erna Viterbi Faculty of Electrical Engineering, Technion—Israel Institute of Technology, Haifa, 3200003, Israel
[c] Department of Computer Systems, Tallinn University of Technology, Akadeemia tee 15a, 12618 Tallinn, Estonia

ARTICLE INFO

Article history:
Received 30 November 2020
Received in revised form 12 January 2021
Accepted 27 January 2021
Available online 13 February 2021

Keywords:
Recommender systems
Demand side management
Energy efficiency
Digital twins
Innovative energy services

ABSTRACT

Innovative solutions targeting improvements in the behavior of energy consumers will be required to achieve desired efficiency in the use of energy. Among other measures for stimulating consumers' behavior changes based on attention triggers, personalized recommendations are essential to enhance sustainable progress towards energy efficiency. In light of this challenge, the current study focuses on innovative energy services that are based on intelligent recommendation systems and digital twins. We review several trends associated with the modeling and diffusion of energy services, taking into account the positive interrelationships existing between recommendation provisions and demand-side consumer energy behavior. This is achieved by means of a content analysis of the state-of-the-art works, focusing on the IEEE Xplore and Scopus databases. Based on this review, we present new empirical evidence to validate data-driven twin technologies as novel ways of implementing consumer-oriented demand-side management via sophisticated abstraction of consumers energy behaviors, and identify various barriers associated with the adoption of energy services, especially as they relate to the implementation and overall adoption of the digital-twins concept. Lastly, we use the review to summarize a coherent policy recommendations related to the wide-spread adoption of the digital-twins concept, and demand-side management solutions in general.

Contents

* Corresponding author.
E-mail addresses: abiodun.onile@taltech.ee (A.E. Onile), ramm@ee.technion.ac.il (R. Machlev), eduard.petlenkov@taltech.ee (E. Petlenkov), yoashl@ee.technion.ac.il (Y. Levron), juri.belikov@taltech.ee (J. Belikov).

https://doi.org/10.1016/j.egyr.2021.01.090

List of abbreviations

AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
CE	Cost of energy
DG	Dispatch generators
DNN	Deep neural network
DR	Demand response
DSM	Demand side management
DT	Digital twins
EMS	Energy management system
ES	Energy services
ESCOs	Energy service companies
GHG	Green house gas
HVAC	Heating ventilation and air conditioning
IES	Innovative energy services
IoT	Internet of things
LED	Light emitting diode
NILM	Non-intrusive appliance load monitoring
PRS	Personalized recommendations system
RET	Renewable energy technologies
SDG	Sustainable development goals
SMEs	Small to medium-sized enterprise
SVM	Support vector machine

1. Introduction

Energy consumption in the recent decades has been on the rise and can be associated with electricity being a convenient substitute to fuel (oil and gas), acting both as primary and secondary sources of energy (Chalvatzis and Rubel, 2015). This makes the electricity sector a leading contributor to Green house gas (GHG), and also the sector generating the highest concentration of emission per source, when compared to those recorded by other sectors (Malmodin et al., 2010). An agenda of sustainable development is essential for transitioning into an energy efficient economy, and will entails measures not limited to technologies and policies, but also to innovation as specified by the Sustainable development goals (SDG) of the United Nations (Hills et al., 2018). At the EU level, meeting the European CO2 emission reduction target by 2030 will require changes in the behavior of European consumers (Koroleva et al., 2019). Additionally, measures in the form of international agreements such as the European Emission trading Scheme or the Kyoto Protocol, are also geared towards mitigating the impact of climate change (Delzendeh et al., 2017). Adopting these measures on the other hand poses challenge for the consumers as they sometimes lack requisite technical expertise, monetary and time resources to implement such conservation measures. The implication is that the responsibilities of operations associated with the power systems have been left solely to ill-equipped consumers which promotes the use of energy managers, contract consultants and Energy services (ES) companies to better manage their consumption profile. In spite of these efforts, energy related activities in the EU have steadily increased, owing to rapid innovation in the electronic industry and consumer demand for comfort and efficient ES, leaving the designated observers in an uncomfortable position (Kowalska-Pyzalska, 2018). To this end, there is an increasing need to rethink the concept of energy conservation, with necessary measures put in place. The question however is not whether consumers should be equipped with smart energy solutions and measures such as innovative policies or ES, but rather how these solutions will be deployed.

In particular, Innovative energy services (IES) are an important requirement in the quest to overcome challenges associated with energy inefficiency with intents of supporting consumers transition into actions geared towards energy sustainability. Similarly, digital technologies have advanced tremendously in the recent decades heralding the birth of Digital twins (DT), creating ways for a real-time synchronization and monitoring of the energy system via computerized and virtual world modeling of service, resulting from data, information and consumer behavior (Stark et al., 2017; Brosinsky et al., 2018). Most of all, a better understanding of consumer behaviors is required to speculate their energy consumption pattern, which is an important feature for achieving reduction in energy consumption. Successful transition into energy-relevant behavioral change can be facilitated by intelligent recommendations. Intelligent recommendation system provides information associated with the selection of alternative cause of action allowing consumers to be directed to services that are customized for them in a large space of potential alternatives (Aguilar et al., 2017). This approach has found application in the electronic commerce industries where recommendation system suggests recommendation tips that help consumers conveniently achieve their goal for energy optimization. The introduction of personalized recommendation to Demand side management (DSM) holds immense potential to enhance consumers' energy efficiency.

It is worthy of note that only few publication contains evidence describing association linking energy consumer, energy conservation, DT and recommendation system. From the literature perspective, a review of incentives and barriers towards the adoption of IES based on consumers' environmental behavior has been presented, which identified intention-behavior gap as major problem towards such adoption (Kowalska-Pyzalska, 2018). In-spite the knowledge of benefits associated and consumers willingness to adopt IES, it does not automatically translate into certain desired behavior giving way to intention-behavior gap (Kowalska-Pyzalska, 2018). A similar work which addresses energy conservation behavior in group of agents using economic behavior model based on theory of cellular automata has been presented (Tetiana et al., 2018). This work is limited in scope as it solely addressed consumer economic and social behavior. In addition, work Irizar-Arrieta et al. (2020) presents an approach utilizing human computer interactions for the improvement of energy consumption with a focus on energy efficiency. Existing solutions attempting to explore the concept of consumer-oriented energy efficiency models are PEAKapp (2017), SOCIALENERGY (2017) and IntelliSOURCE. These solutions are however heavily customized for utilities' administrative users rather than ordinary energy consumers. It can be concluded that energy supply in the future will be characterized by economy and consumer-focused, rather than generation dominated (Chalvatzis and Rubel, 2015).

In light of the challenges mentioned above, the current study focuses on innovative ES that are based on intelligent recommendation systems and digital twins. Unlike the approach adopted in Chalvatzis and Rubel (2015), Kowalska-Pyzalska (2018), Tetiana et al. (2018), PEAKapp (2017) and SOCIALENERGY (2017), this study focuses on the trends associated with the modeling and diffusion of IES, taking into account the positive interrelationships existing between recommendation provisions and demand-side consumer energy behavior. This is achieved by means of a content analysis of the state-of-the-art works, focusing on the IEEE Xplore and Scopus databases. Based on this review, we present new empirical evidence to validate data-driven DT technologies as novel ways of implementing consumer-oriented DSM via sophisticated abstraction of consumers energy behaviors, and identify various barriers associated with the adoption of IES, especially as they relate to the implementation and overall adoption of the digital-twins concept. Lastly, we use the review to summarize a coherent policy recommendations related to the wide-spread adoption of the digital-twins concept, and demand-side management solutions in general.

The rest of the paper is organized as follows. Section 2 discusses the idea of intelligent ES. Section 3 provides an overview of data modeling and digital twinning, while Section 4 discusses the recommendation features and energy saving tools. Section 5 presents an analysis of the results, and Section 6 concludes the paper.

2. Overview of innovative energy services for consumer-oriented design

In this section, IES is being discussed by exploring various components of consumers driven innovative models and their linkages to energy efficiency services based on behavior alterations at the consumer end.

2.1. Energy services

The concept of ES can be associated with how effectively demand side reduction and management can be understood, anticipated and modeled (Fujimori et al., 2014). Business model that encourages selling functions provided by energy has found appealing acceptance especially among consumers. Similarly, retreating from the fundamental business of selling energy (Morley, 2018) into servitization (Plepys et al., 2015), has seen Energy service companies (ESCOs) being identified with the tasks of selling a range of "efficiency services" in form of advice, energy saving deliveries, and equipment installations, based on performance contracts (IEA, 2013; Mourtzis et al., 2018). Although the term "energy services" has sparked various debates in scientific literature, the work Fell (2017) tried to clarify this discrepancy revealed that the differences associated with the term could be associated with different field of science and approach for energy usage.

Recent reviews on the idea of ES have been presented in Fell (2017), Kalt et al. (2019). The work Fell (2017) reported that, ES are functions that require energy for their execution acting as a means towards achieving a desired state or end services. Work (Morley, 2018) presented a review focusing on the socio-cultural and dynamic nature of ES referred to as meta-services, which are not only determined via energy provision, governance or consumption but also by other organizations that are not providing energy, with intent to efficiently stabilize the level of demand for ES.

2.2. Innovative energy services

Energy services providers are experiencing transition on global scale (Kowalska-Pyzalska, 2018). In most cases, this transition is aided by the availability of smart technological solutions allowing energy consumers to freely assume an active role in the energy market. These services form the building blocks of a rapidly advancing digital energy ecosystem providing opportunity for digitally compliant consumers and progressive/forward thinking utilities to make a claim. Effective transition of the energy system towards sustainability therefore calls for innovation among others factors such as economic, technology and policy (Hills et al., 2018; Onile et al., 2020). Innovation has been defined as act of using iterative design process, deployment, improvement, and testing to put ideas into practical use (Grübler and Wilson, 2013; Miremadi et al., 2018). It has also been seen as the basis of all activities and can originate from both internal factors such as: inconsistencies, technical demands, situations relating to force majeure and market and industrial changes; external factors on the other hand includes: globalization, world digitization, identification of new knowledge area and changes in recipients (Rudskaia and Rodionov, 2018). In order to achieve the UN SDG agenda of 2030 for sustainable development, there is need for innovation geared towards energy conservation. Innovation in energy system provides a workable option for addressing challenges associated with energy security in the face of increasing electricity demand coupled with problems of environmental degradation (Miremadi et al., 2018) and economic challenges (Chalvatzis and Rubel, 2015). Similarly, innovation in the energy sector will be required in order to meetup with the Paris agreement aiming at 1.5 °C reduction and the energy for all agenda of the Sustainable Development Goals. Additionally, a "Mission Innovation" and investment to double R&D for expediting action on the uptake of clean energy have also been signed by the G20 (King, 2017; Bak, 2017). The need for innovative, persuasive, deep and swift transformation from the classical approach for resourcing, transforming, consuming energy is therefore imminent (Geels et al., 2017; Wilson and Tyfield, 2018). Recent reviews of IES have been presented Bigoloni and Filipponi (2017), Kowalska-Pyzalska (2018), Gaspari et al. (2017).

In this paper, the concept of IES was compiled, based on the recent literature and understanding of consumer-oriented approach. A consumer-oriented model which utilizes intelligent components to non-intrusively provide recommendations capable of influencing consumers behavior to adopt energy saving options (Paukstadt et al., 2019; Mrazovac et al., 2012) in categories such as: Social (Soc), Economic (Eco) and Technical (Tech) was considered. For example, in order to capture a comprehensive estimation of energy wastage we explored the identified IES model using two major tools (contributing technologies) which include: DT recreation of energy consumers (see Section 3), and recommendation system to provide actionable insight (see Section 4). Previous works selected for review in Sections 3 and 4 are directly related to "recommendation systems" and "energy services". Fig. 1 describes the schematics layout of the study. It depicts consumers' consumption data and DT modeling with broader discussion in Section 3 and their associated recommendations with further discussion in Section 4.

In what follows, this section further elaborates on various aspects of innovation in the energy sector.

Technological innovations: The ecosystem of innovation describes the environment where interactions associated with flow of technologies and knowledge occur (Kotilainen et al., 2016). Digital technologies have been seen to be effective as an enabler of innovation across various economic sectors. The concept of digitization in the energy sector has helped in stabilizing the transmission grid simply by stabilizing reserve from fluctuating energy sources such as solar and wind (European Union, 2018). Connecting objects at the micro level using Internet of things (IoT) opens an unprecedented gateway allowing electric devices to contribute to the energy system building even bigger ecosystem for the distributed energy resources. Thus, digital innovation in the energy industry aided by the emergence of the IoT has provided convenient approach for integrating non-human elements in the managerial strategies of the digital innovation and its respective ecosystem (Kolloch and Dellermann, 2018). In previous research, Bergek et al. (2015) worked on technological innovation system and its interactions with the wider context structures. The paper Yang et al. (2019) proposes the analysis of energy technical innovation from the renewable energy and fossil energy point of view. It was reported that the impact of

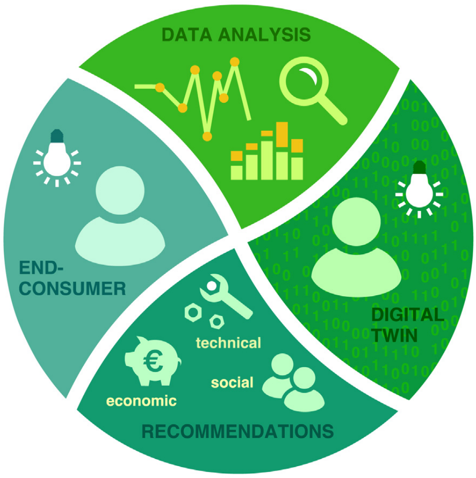

Fig. 1. Overall scheme of a common consumer-oriented framework for recommendation of innovative energy services.

innovation technology on fossil energy exceeds that of renewable energy when considering price, making the renewable energy price fall below the optimal rate while placing demand on the requirement of price mechanism for the development of renewable energy technology in China. It was further identified that the government policy support has to be an enabler for the development of the proposed technical innovative technology. Meanwhile, recent academic literature has payed close attention to system concept approach to policy making and innovation systems (Sharif, 2006). Innovation in the energy sector requires established set of indicators for evaluating energy performance in relation to the innovation system (Miremadi et al., 2018; Borup et al., 2013). The work (Miremadi et al., 2018) identified about 120 indicators (categorized as policy, impact, input, output, structural and systematic indicators) associated with four criteria (availability, understanding, relevance and measurability) used to describe notable weaknesses among available indicators. At the technology level, 90 indicators were used to match seven functions available for system technological innovations which could also be used to generate policy recommendations.

Although, traditional approach based on expert advice has been considered as effective but it is rarely scalable to meetup with large number of consumer (Starke et al., 2017). Research targeting persuasive technology, however indicated that technical innovative solutions holds the clue to helping consumers achieve their energy efficiency goals.

Economic innovation for energy: Rational use of energy produces economic development and to satisfy such demand for development, energy consumption needs to undergo structural upgrading and innovation funding for better economic benefits (Foxon, 2013; Jabbour et al., 2015; Ma, 2019). From the political point of view, funding framework for low carbon innovations based on low-carbon economy can be provided by government to integrate environmental policy and innovation policy which can be developed from divergent point of view (Willis et al., 2007). Successful adoption of corporate actions and the use of carbon-low Eco-innovation in the fight against climate change, relies on the nature of resources and support available to organization (Polzin, 2017).

Work (Bridge et al., 2013) reported that energy system and the concept of spatial differentiation has implication on growth and development of the economy. Innovation associated with the energy sector are developed from various clusters that are geographically defined (Baptista and Swann, 1998; Cooke, 2001). These clusters are seen as global locus for low carbon energy innovations and can be considered as a major point for hitching regional economic fortune. Work Jabbour et al. (2015) described the application of Eco-innovation to sustainable supply chain for a low-carbon economy. Similar study presented by Ma (2019) identified optimized economic model for industrial innovation based on economy of clean and renewable energy (geothermal energy) as key contributor to sustainable economic development.

Social innovation for energy: Social innovation will be required to effectively transition into low carbon energy system (Hewitt et al., 2019; Selvakkumaran and Ahlgren, 2020; Wittmayer et al., 2020). This includes activities associated with social goals for achieving community general well being and civic empowerment. More often than not, the technical and social aspect of energy system have been researched separately, the later however is crucial to the adoption and acceptance of such innovation by the society. Work Abbar et al. (2018) presented innovation model based on city neighborhood and social networks for the adoption of Renewable energy technologies (RET). They came up with a twitter based constraints obtained from censor geography of Qatar. The rate of RET innovation diffusion was later determined using a combination of twitter network and household diffusion patterns based on adapted linear threshold technique for spreading information. A collection of key citizen motivated renewable energy solutions and operational criteria termed as community energy viewed in the lens of social innovation has been surveyed in Hewitt et al. (2019). Work Kotilainen et al. (2016) addressed the function of residential prosumer in instituting innovation in energy ecosystem to ensure flexibility in the energy system of the future. Their proposed social-technical and diffusion approach targets the implementation of government actions towards slowing down climate change on global scale and enhancing advancements in technology in ICT and consumer electronics. Finally, study presented in Wittmayer et al. (2020) focused on the application of social innovation in the context of socio-technical energy systems.

Innovation diffusion in itself is a process associated with spreading of the innovation within a period of time. Innovation can therefore be adopted among a group of people referred to as innovators, primary adopters, secondary adopters and sluggards (Kotilainen et al., 2016). The theory associated with the diffusion of innovation has been focused on the analysis of social network, allowing build up of peer pressure resulting from a positive feedback from initial benefactors of such innovation (Abrahamson and Rosenkopf, 1997; Abbar et al., 2018). With significant interconnection with eco-innovation and environmental policies, demand side innovation policies have also been seen to proffer solution targeted towards overcoming difficulties relating private market innovation diffusion. A study on consumer innovation diffusion for sustainable energy solutions using small-scale RET has been presented (Hyysalo et al., 2017). Their investigation revealed a 34% consumer adoption rate based on "innovative peer diffusion". Work Kahma and Matschoss (2017) presented the idea of smart ES in the light of innovative technology diffusion. The author further described innovation adoption as a concept of technological diffusion noting that the probability of success or failure (non-use) of novel technologies depends on its ability to permeate the energy market. To solve this problem, work (Clausen and Fichter, 2019) observed innovation diffusion based generalized inhibition and driving factors. Similarly, work Vaidyanathan et al. (2019) presented a study on multi functional and analytic framework of renewable energy technology innovation diffusion for energy deficient communities based on decentralized innovations (Vargo et al., 2020). Fig. 2 describes the adoption rate

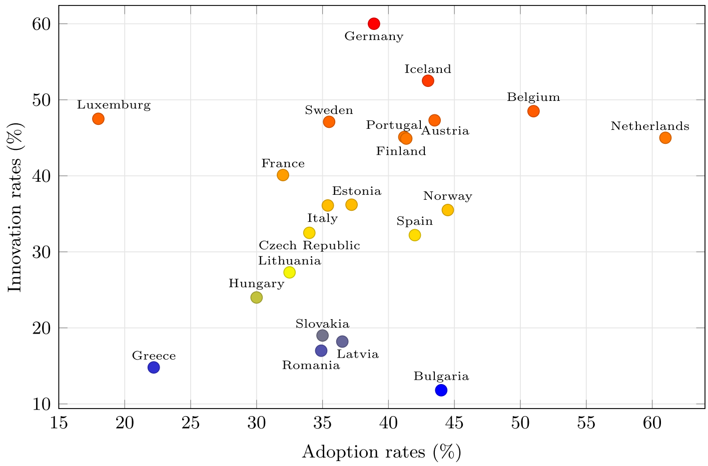

Fig. 2. Innovative services adoption rate.

of innovation services across EU member state (Autant-Bernard et al., 2010).

Energy services for basic consumer (in perspective): Energy is not consumed simply by purchasing it, but rather must be converted from nature into forms that provide services such as power to appliances (Haas et al., 2008; Kaygusuz, 2011; Fell, 2017; Morley, 2018; Rinkinen and Torriti, 2019). In general, effective use of energy is associated with provision of services such as ventilation, heating, lighting and motive power (WHO, 2018). The following paragraphs describe examples of ES.

Lighting: Irrespective of income or class, illumination is considered as an essential need for life, making it the major source of energy expenditure and a significant portion of consumer budget. This paragraph describes various services in lighting with the goal of optimizing energy consumption. The work of Polzin et al. (2016) described the application of innovative end use energy demand reduction technologies associated with energy efficiency services in municipalities using Light emitting diode (LED) street lighting. Another work focusing on low cost energy efficiency compact fluorescent lamps with promises to reduce GHG emission and overall energy demand has been presented (Figueroa et al., 2019). An approach utilizing the application of ICT and LED in achieving deep energy savings for outdoor street lighting based on life-cycle services and energy data was presented by Pandharipande et al. (2019). Similarly, smart lighting services are often seen to incorporate different levels of energy savings. In line with this, work (Cacciatore et al., 2017) identified three unique heuristics incorporated in smart lighting based on the technology deployed in lamps. An approach implementing IoT alongside the WWW integrated lighting promises to provide energy efficient lighting (Murthy et al., 2015).

Cooking: Immense potentials for energy savings lie in services associated with cooking and heating for consumers across various income class or group (Strydom et al., 2020). Study revealed that about 2.3 billion people do not still have access to clean cooking services while projecting that about 2.5 million pollution related deaths on yearly basis may be recorded by 2030 (Batchelor et al., 2019; WHO, 2018). In the same vein, the SDG7, promotes reliable and affordable, modern cooking services and technologies (Karanja et al., 2019; UN United Nations Sustainable Development Goals, 2018). Cooking services provided using electricity holds potential for disruptive transformation for households. Residents do not only enjoy benefits associated with less exposure to dangerous emissions but also experience a cleaner cooking environment when electric cooking is deployed. Research into the development of modern energy cooking services based on energy storage and off-grid has been described in (Batchelor et al., 2019). A transition from conventional cooking approach into the use of battery electric enabled eCook (Batchelor et al., 2018; Brown and Sumanik-Leary, 2016; Brown et al., 2017) and renewable such as the hybridized solar electric stove proves the technical viability of renewable in cooking as modern and cleaner option.

Heating and Cooling: Innovative services with application to Heating ventilation and air conditioning (HVAC) are requirements for ensuring a productive and healthy environment for occupants while paying attention to measures for attaining reduction in energy consumption and its associated cost. In order to attain desirable energy saving feat, it will be required to deploy energy technologies and systems that optimizes energy consumption some of which includes heat/energy recovery ventilators, evaporative cooling, night time radiative cooling, etc. Ma et al. (2019). Meanwhile, the following systematic reviews have investigated innovative action in heating and cooling. A study conducted using air handling unit for achieving energy savings subject to the introduction of energy efficiency measures was presented by Shea et al. (2019). Cooling was achieved by pumping air through cooling coils located in the air handling unit for cooling the air while heating requirements were implemented by varying the supply of cooled air for heating demand of various zones allowing reduction in excess usage of energy. In order to meet the information demand associated with heating system, integrated information services framework based on open group architecture and service oriented software architecture has been considered to eliminate the challenges associated with information island in central heating systems allowing for efficient sharing of information and provides integration control.

3. Data modeling and digital twinning

This section presents an overview of various tools and supporting technologies for consumption reduction based on modeling consumers as DT in the IES framework (see Fig. 1) presented in Section 2.

3.1. Digital twinning

Digitization has recorded highly pervasive association and increased integration with modern energy systems resulting into increasing and effortless connectivity between virtual machines, data and their physical environment. DT can be described as front runner of Industry 4.0 and virtual representation of a rare or real-life assets such as services, products or machine with the models that are capable of achieving behavior alteration (Uhlemann et al., 2017; Yan et al., 2018; Rasheed et al., 2020) using real-time data and intelligent analytics (Brosinsky et al., 2018; Fuller et al., 2020) supported with visualization software (Zhou et al., 2019) and interfaces which generates information associated with the state of the machine (Karanjkar et al., 2018) such as performance metrics, machine operation state, energy consumption, product quality targeting improvements in energy system efficiency. The term DT was originally conceived in Grieves (2015) and has been strategically rated as one of the top ten technologies of year 2018 (subject to predictions on future trends in research) with a potential to attain a 15 billion dollar market target by 2023 (Khajavi et al., 2019).

A consumer-oriented DT framework can be derived from modeling methodology that integrates historical loads and social media (meta) data analysis, short/long-term energy forecasting, machine learning models, and data visualization to achieve DT recreation of energy profile of consumers based on energy behavior pattern (Havard et al., 2019). This approach is underpinned by interoperation of advanced load prediction and analytic models. This way consumers are required to possess less technical knowledge of the energy system, rather advanced intelligent, analytic models extract knowledge from the digital signature of electricity consumption. A review has been presented in Brosinsky et al. (2018) focusing on developments and the application of DT to the control of power system. Work (Francisco et al., 2020) explains the application of DT with respect to energy benchmarking as an approach to getting informed about optimal energy decision making towards better strategies for energy retrofitting and real-time energy managements. A multilayered approach energy efficient model based on DT modeling of energy consumption has been presented by Andryushkevich et al. (2019), Lu et al. (2019). Work (Andryushkevich et al., 2019) further used ontological modeling language for recommendation provision in digital decentralized energy sector. A DT application platform for smart-grid using online analysis of the power grid has been presented (Zhou et al., 2019). Recent implementation of this concept in the energy sector includes Honeywell Forge APM-Asset Performance Management software for energy monitoring (Honeywell, 2019), HVDC Light DT and Edge based available peak power an ABB solution for PV module (ABB, 2020).

Key enabling technologies: To achieve significant reduction in energy consumption at the consumer end using DT framework, it is important to describe key technologies (Qi et al., 2019; Fuller et al., 2020) and parameters supporting the described framework. The input to the DT model is the output obtained from the data gathering and insight stage, with an output targeting energy reduction. Similarly, it is important to present the key enabling technologies associated with the smooth running of the described architecture. These include IoT platform, energy forecasting, and advanced data analytics.

IoT framework: Application of information technology such as the IoT coupled with smart devices enabled with the ability to obtain data produced during a product's lifetime, and supported by the data mining ability of Artificial intelligence (AI) are all paving the way for a new era of data driven product design, manufacturing and service (Tao et al., 2017). The IoT platforms which generate data from physical system in real-time combined with historic data set provided from previous energy consumption are all utilized in the development of DT concept (Ruohomaki et al., 2018). Similarly, technologies such as Energy Internet (Hong et al., 2018; Kaur et al., 2019; Qureshi et al., 2020), Smart Grid (Qureshi et al., 2020; Feng and Liao, 2020) and Industrial Internet of things (Zhang et al., 2018b; Cheng et al., 2020) also provides intelligent sensing capabilities and secure transmission network towards effecting consumer-oriented DT framework.

Data and metadata analysis: Data in its raw form is neither useful for recommendation system nor for energy forecast, it is therefore important to understand key variables associated with energy forecast and recommendation. It will be required to commit efforts into data preprocessing in order to extract important features such as social behavior, temperature, demographic information, geographical information, etc. The following describes methods for obtaining key features associated with energy consumers.

Data Gathering and Insights: Data collected form smart meters, weather station and historic consumption are utilized for the development of parameters required for the DT implementation and simulation (Karanjkar et al., 2018). Consumer associated data are collected, measured, processed and analyzed to develop customized and optimal energy strategies (Castelli et al., 2019). Online social media networks are used to obtain consumption data within a social group used by individual DT. This source of information promotes inclusiveness and allows for every consumer within a social group to be carried along.

Large amount of heterogeneous consumption data describing various energy phenomenon are intuitively useful in modeling machine learning based analytic tools. This heterogeneous data obtained from real-world scenarios represents a valuable and precious ingredient, useful in performing services that are deemed complex. The application of AI helps to provide useful insight into this data for automated decision making ability.

Feature engineering: Data cannot be utilized either for recommendation or energy forecast in a raw form, understanding of the key variables influencing energy forecast is therefore necessary. Efforts can be committed into the understanding of the salient features that can influence energy consumption. These include procedures involving preparation of high dimensionality data for data mining operations. In this study, analysis of key categories of features/variables for rating consumers is discussed (Zhang et al., 2018a). Such data includes forecast and key historical energy data comprising of hourly electric demand data obtained from utility, social media features, residential features along with policy related features, weather data including outdoor dry bulb, outdoor relative humidity, outdoor air density, ground temperature, zonal total internal heat gain and building data such as lighting, energy consumption and number of occupants, to mention but few. Additional features such as energy profiles for weekdays, weekends, holiday situations, temperature, time (Spichakova et al., 2019) and demographic information of consumers which includes age, family size and historic consumption data were also taken into consideration. These features are considered as factors influencing the energy dynamics of consumers. Table 1 summarizes the review of related works on DT.

Review energy forecasting: Energy forecasting can be broadly classified into the following three main categories short-, medium- and long-term load forecasting. Short-term load forecasting allows energy consumption to be determined for a period ranging from 1 h to 1 week ahead (Ahmad et al., 2018; Jiao et al., 2018; Bouktif et al., 2019) while medium-term load forecasting normally last for a period between 2 weeks and three years with the main intent of planning, maintaining and dispatching load *ex ante* (Essallah and Khedher, 2019; Spichakova et al., 2019). Long-term load forecasting is important ingredient in the efforts aimed

Table 1
Related works on digital twins.

Ref.	Methodology	Platform	Benefits	Drawbacks	User type
Brosinsky et al. (2018)	Dynamic digital mirror	Energy management system (EMS)	Proposed platform operates faster than SCADA	Difficulties in obtaining detailed modeling of the power system	Control centers for power systems
Andryushkevich et al. (2019)	Ontological modeling language	Hybrid renewable energy system	Provide means for updating DT in the energy sector	Lack of tools for automating data synchronization	Energy prosumer
Francisco et al. (2020)	Regression	University campus power supply	Examines temporal dimension for bench marking energy	Difficulties in determining level of agreement for building efficiency	Campus
Zhou et al. (2019)	Online analysis digital twin	EMS system for power grid	Fast complete online analysis using data-driven large scale model	Sub-second delay exists	Dispatching control centers

at achieving desired understanding of future energy demand allowing a long term view into the consumption of electricity towards the development, planning and drafting efficient policies of national economies (Silva et al., 2018; Chen et al., 2019).

A robust load forecasting model spanning different time horizon is crucial for effective operation of the power system (Fallah et al., 2018; Sangrody et al., 2018) and has been identified to play significant role in optimizing the practical operation of DT (Xie et al., 2019). Early research into energy load prediction have been focused on regression analysis while a combination of multiple meta heuristic techniques such as genetic support vector machine (SVM) and Firefly algorithm neural network have also proven to be effective (Fallah et al., 2018). Work Xie et al. (2019) proposed a demand forecasting model for DT application in power grid using Deep neural network (DNN) based ordinary differential equation. Study outcomes from a short-term residential load demand forecast indicated an appreciable level of accuracy for vast array of prediction applications especially in future energy consumption forecast, and market price for grid economic optimization. Work Damiani et al. (2019) presented a DT implementation of a short-term electricity price forecasting model for electricity cost optimization in logistic centers using autoregression model. The authors identified electricity price as major performance indicator in the operation of logistic centers with high energy demand. Based on this information, they presented an innovative and synergic power consumption inner tool for best price predictive analysis. Work Kychkin and Nikolaev (2020) proposed DT enabled IoT-based ventilation control for energy saving in mining operation. The DT implementations incorporates an online short-term load forecasting of energy consumption using integrated linear auto regression, linear regression, and multilayer perceptron predictive models. Study outcomes revealed that forecast was useful in optimizing mine air regulation algorithm and energy. Work O'Dwyer et al. (2020) proposed an integrated DT and energy management tool for achieving coordination in multi-vector smart energy system. The proposed tool is underpinned by forecasting, optimization and coordination service subsystems implemented using Artificial neural network (ANN), gradient boosting and k-means clustering algorithms for about 97% curtailment of high system constraint violation. On the other hand, work Nwauka et al. (2018) argued on application of Industry 4.0 for the integration of distributed energy resources applications based on the exploration of basic operational and technical requirements of virtual power plants. The proposed intelligent management framework carried out scheduling optimization using real-time day-ahead forecast of load, electricity spot prices, and generation profile. Table 2 describes an overview of energy forecast application to DT.

3.2. Digital twin for consumer energy services

The consumer ES described in this section focuses on the use of DT technology (O'Dwyer et al., 2020; Kabugo et al., 2020; Teng et al., 2021) for post generation associated services employed for consumer end demand management, service reliability and convenience geared towards energy efficiency. Based on this, relevant services associated with energy efficiency can be provided to consumers which could belong to the following categories (Tao et al., 2017; Bakhtadze et al., 2019; Tao et al., 2019):

- Energy consumption analysis and forecast associated services (Kabugo et al., 2020): The result of high achievable precision between the virtual and physical world which allows for the projection of energy consumption on various scale such as on daily, weekly or monthly basis. In addition, the future consumption of energy can also be estimated allowing for potential discovery of better energy behaviors and choices.
- Energy management services based on behavioral analysis (Li et al., 2020; Xiang et al., 2020): Users are analyzed based on their energy consumption habits using DT real-time monitoring services allowing for the correction of poor energy behavior and lifestyle for consumers in real-time. This can be achieved by simply analyzing the consumption habits for computing life actions associated with energy behaviors in the one hand and helping utilities manage and effectively hands off DSM using DT energy services while giving them the ability to improve on quality of service on the other hand.
- Provision of intelligent service update and optimization (Min et al., 2019): DT allows for the generation of consumer habits based on their different and independent patterns of energy use. Holding the opportunity for the real-time correction of consumer poor energy habits. This majorly is as result of analysis of specific user consumption habit and checking whether they are within the healthy consumption band.

4. Recommendation features/tips

In this section, we present recommendation system as a major component in the IES framework (Fig. 1) described earlier in Section 2.

The key element of a recommender system is its ability to understand the preferences of an active user simply by analyzing the user and/or other user's behavior (Lu et al., 2019; Ayres et al., 2018; Hafshejani et al., 2018). This domain of study evolved in the

Table 2
Related work on energy forecasting for digital twins.

Ref.	Methodology	Platform	Benefits	Drawbacks	User type
Xie et al. (2019)	DNN, Ordinary differential equation	Smart grid	Balance and stable forecast performance for volatile electricity load	High uncertainty in data attributes	Residential consumers and utilities
Damiani et al. (2019)	Autoregression model	Maritime infrastructure	Reduces high initial energy demand for planning stage of logistic center	Difficulties in eliminating periodic components of series due to periodic delays	Commercial sector: Maritime
Kychkin and Nikolaev (2020)	Linear autoregression, Linear regression, Naïve model, & Multi-layer perceptron	Cyber–physical system for mining sector	Proposed model guarantees energy efficiency	–	Industrial sector: Mining
O'Dwyer et al. (2020)	ANN, K-means, gradient boosting, random forest	Smart energy management system	Optimal operation decision provision via day ahead forecasting and curtails high system violation by 97%	Lack of extensive energy forecasting	Residential consumers and utilities
Nwauka et al. (2018)	Predictive analytics model	Virtual power plants	Hybrid model produces better coefficient estimation	Policies, institutional, regulatory barriers to deployment	Utility

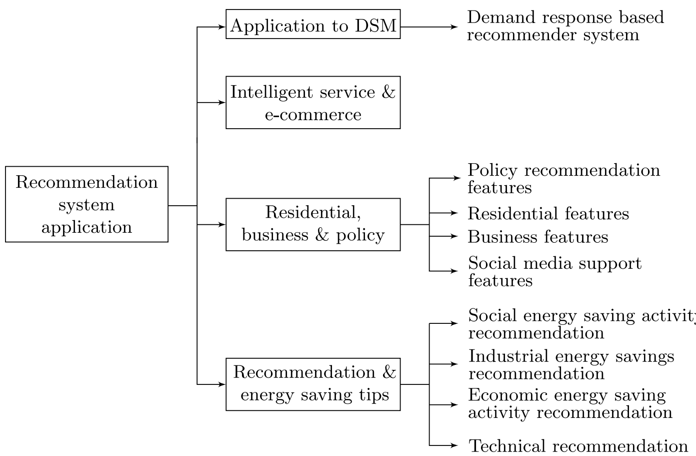

Fig. 3. Recommendation system application.

mid-1990s, when, researchers were interested in the application of rating structure (Lu et al., 2019; Adomavicius and Tuzhilin, 2005). E-commerce and web services were the first to utilize recommendation systems. This was soon followed by social network and service selection (Mezni and Abdeljaoued, 2018). Recommendation systems have been mainly researched based on the following approaches: collaborative filtering and content/knowledge based with associated merit and demerits (Karbhari et al., 2017). Collaborative filtering methods generate recommendations for an item based on similarities existing between users' history (Lu et al., 2019; Tarus et al., 2017), content based methods generate recommendations for an item based on similarities existing between item description and user history (Lu et al., 2019) (see Table 5), the knowledge-based approach generates recommendations based on the domain knowledge about how the product meets users' needs (Tarus et al., 2017) (see Table 3).

In a previous study, an approach incorporating intelligent recommendation system for innovative service design based on user behavior change has been examined (Trappey et al., 2013). To further extend the application of IES using recommendation system, we present recommendation system as a major component in the IES framework (Fig. 1) described earlier in Section 2.

Recommendation system for energy applications: This section examines the four major categories for providing recommendation tips to energy consumers, namely: business and industries, residential, and policy categories. Recommendation systems area of applications in our context describes the case studies and the area of application especially within the energy domain as depicted in Fig. 3. The section further elaborates on the following application areas for recommendation provision:

(a) Application to DSM
(b) Application to intelligent services and e-commerce

(c) Application to consumer behavior
(d) Residential, industrial, business and policy
(e) Social, technical and economical

4.1. Application to energy management and intelligent services

(a) Application to DSM: There are numerous electricity plans available to consumers to take advantage of which often introduces confusion on which is the most suitable service for individual energy consumers to adopt in managing their energy supply subject to lifestyle (Ros et al., 2018). This section describes various aspects of recommender system in relation to energy.

Demand response based recommender system: A vast amount of efforts have been committed to studying technological approach for reducing electricity demand by switching from peak to off-peak. In doing this, platforms that monitor and control household energy consumption and systems that provide energy efficiency by encouraging behavioral changes for energy efficiency are required (Alsalemi et al., 2019; Jabir et al., 2018a). DSM is a major area of interest for smart grid (Teh et al., 2018; Metwaly and Teh, 2020; Jabir et al., 2018b), with demand side Personalized recommendations system (PRS) leading the way in inferring residential user's needs and interests on their energy saving appliances (Luo et al., 2017). There is a vast amount of research work carried out on Demand response (DR) based recommender systems (Behl et al., 2016; Luo et al., 2017). The work of Behl et al. (2016) presented a data driven approach to a recommender system for DSM. They employed the use of regression tree algorithm alongside open source MATLAB based DR-Adviser for the control of commercial building and providing suitable recommendations to residents. The study presented by Luo et al. (2017), attempts to integrate demand side based PRS and service computing paradigm. Authors revealed that residential user potential interest and demand for energy conservation is been inferred using PRS approach for service recommendation. Demand side PRS comes in various format, such as retail plan for electricity, suggestions or recommendation on energy consumption (Luo et al., 2020), or appliances optimized for saving. Another approach to achieving this is to apply a Non-intrusive appliance load monitoring (NILM) technique to disaggregate the smart meter data from the utilization profile of end user home appliances and compare appliance similarities measure using generalized particle filtering (Luo et al., 2017). The goal of this service is to ensure consumer satisfaction by simply stimulating or encouraging them to acquire energy saving appliances, so as to reduce the cost of energy consumption for users. Table 3 describes related works on demand side recommender system.

(b) Application of recommendation system to intelligent services and e-commerce: Intelligent energy management services based on actionable recommendation and analytics have been seen to give consumers the motivation for energy conservation, and identify problems in their energy behaviors (Shin and Hwang, 2012). By suggesting information about suitable products to consumers, recommender systems have emerged as the cornerstone of e-commerce platforms that provide services associated with competition (Li et al., 2016; Mahmood et al., 2015). One of the major advantages of intelligent techniques in home energy management is the ability to aid reduction in power consumption and support DSM (Ayres et al., 2018). Work Ayres et al. (2018) developed a novel intelligent architecture for energy conservation in homes based on recommended suggestions aimed at improving energy efficiency and reducing Cost of energy (CE). Within this context (Zamil et al., 2018) used intelligent solutions based on mobile multimedia technologies to determine the activities of residents in a household.

Intelligent services targeted towards energy management could require some level of adjustments from home appliances to cater for energy conservation (Ayres et al., 2018). Within this context, several reviews have been presented. Work Romero et al. (2018) presented a DR framework for the integration of intelligent EMS for enabling reduction in the CE and holistic optimization of DR in homes. A study of consumer engagement based on consumer experience obtained from energy efficiency is presented in Kompos et al. (2019). The authors presented a realistic and innovation solution geared towards the delivery of consumer-oriented and behavioral transforming platform developed using economic building with affordable sensors. In addition, consumer-centric intelligent control features alongside HVAC supportive control was used to conserve energy. Work Marinakis et al. (2020) presented a smart ES based intelligent energy management using big data technologies for the development and exploration of smart ES while incorporating a decision support system which allows convenient information gathering for generating recommendations. Table 4 provides a summary of related works on intelligent ES and e-commerce, while Table 5 summarizes recent works on application of recommender systems.

4.2. Application to consumer behavior modeling

(c) Application to consumer behavioral reflective attributes: The behavior of consumers has been described as soft characteristic which proves difficulties in measuring objectively in a similar way as energy consumption (Zehnder et al., 2015). Note that not all consumer behaviors result into energy conservation. It is therefore important to identify relevant behavioral patterns that result into energy savings (Zehnder et al., 2015). Important patterns must result into at least an action which results into energy savings and comprises of normal events. The main task in this situation is for recommender system to identify moments where consumers forget to follow a regular pattern and suggest actions that lead to energy reduction. Traditional approach to obtaining human behavior is via the use of price response reproduction in relation to using discrete choice model for capturing technology adoption and constant elasticity of substitution (Venturini et al., 2018). As indicated in Kashani and Ozturk (2017), two third of energy consumption in residents are associated with human behavior. Work Zhang et al. (2019) examined the role of behavior in the uptake of energy efficiency by monitoring their energy consumption pattern and providing suitable recommendations. A better understating of behavioral, social and cultural factors associated with energy efficiency is therefore required (Kashani and Ozturk, 2017). The value associated with mining consumer behavioral pattern from power system data is increasing and its usefulness for operation in power system is eminent (Xu et al., 2017). According to the literature, the authors in Xu et al. (2017) presented a complementary analysis of energy consumer electricity behavior using k-means algorithms with outcomes showing potential for energy consumption optimization. Work Galperova and Galperov (2018) reported that modeling the behavior of consumer is required for the assessment of electricity systems' mode of operation while modeling consumer active behavior using agent-based technique indicating their role in the smart grid concept allowing for a feedback connection between the grid and consumers. Work Alsalemi et al. (2019) presented a survey on recommender system and change in habitual behavior for energy conservation based on reviewed literature that aims at understanding energy consumers' behaviors with intention of changing it based on recommended energy saving tips. They further developed the theory of "habit-loop" and "micro-moment" to determine the moment when recommendation is optimal, and reward is effective for effecting gradual energy change among consumers.

Table 3
Related works on demand side recommender system.

Ref.	Methodology	Platform	Benefits	Drawbacks	User type
Romero et al. (2018)	OpenADR model	EMS-equipped smart homes	Human-centric demand management approach	EMS and Smart home devices are not interoperable	Residential and tertiary energy consumers
Luo et al. (2016)	NILM	NILM: Smart grid	Investigates application of recommendations to smart grid DSM	Computational cost, data sparsity & cold start problems	E-commerce & electricity retail
Behl et al. (2016)	Regression tree	Large scale energy systems	Recorded 92.8–98.9% accuracy saving up to 380 kW load	Complication in defining partition line/region	Commercial building
Luo et al. (2017)	SVM & Particle swarm optimization	NILM: Electrical appliance	PRS achieved a high level of recommendation accuracy up to 97.0%	Lack of representative data for laundry dryer lowers recommendation accuracy	Smart grid residential consumer

Table 4
Related work on intelligent services and e-commerce.

Ref.	Methodology	Knowledge Gap	Platform	Benefits	Drawbacks	User type
Li et al. (2018a)	Bayesian updating	Effect of recommender systems on manufacturer	Electronic market place, channel structure for retailer and manufacturer	Additional sales	Consumers get benefits at the expense of retailer and manufacturers	Manufacturers, retailers and consumers
Gupta et al. (2018)	Questionnaire surveys, community events & house monitoring	Illustrative Study	households, Decorum model management	Provides residents experience based on visual energy feedback provision	Small number of participants	House holders
Hussain et al. (2018)	Multi objective genetic algorithm, Pareto optimization	Improvement of performance parameters	HEMS	Proposed algorithm allows selection of optimal size dispatch generators	Long computational time	Energy consumers
Cacciatore et al. (2017)	Heuristics, occupancy and distributed control strategy	Achieve coordination for individual lamp dimming	Custom-built simulator	Cost reduction of street lighting	Current implementation does not account for users passing close to the lamp	Pedestrians
Kolloch and Dellermann (2018)	Actor network theory	Applicability of controversy method to other innovation	HEMS	Contributes to management aspect of digital innovation	limits innovation by setting predefined goals for decentralizing energy supply	Consumers

Table 5
Related works on recommender systems.

Ref.	Methodology	Platform	Benefits	Drawbacks	User type
Primo et al. (2012)	Collaborative filtering, content based and Hybrid	Semantic web	Application of data and object properties as a solution to educational recommender system	The platform is unable to integrate different web services to obtain a single learning application	Educational environments
Sellami et al. (2013)	Content based, collaborative filtering and semantic-social algorithms	Semantic web and social network technology	Semantic recommender system performs better	Smaller number of connected users can reduce precision	Social network users

4.3. Residential, business and policy

This section examines the legal, regulatory regimens, and policies available across the globe and further provides directions for policy makers responsible for the deployment of IES. The section further examines an overview of business and residential features supporting effective uptake of IES as summarized in Table 6.

(a) Policy recommendations features for saving energy: Policy can be described as a dynamic process associated with the sum of actions, regulations, laws and other related factors that influence energy conservation among energy consumer. Policy recommendations stand as a well research category for energy conservation (Alsalemi et al., 2019). Most countries are coming up with regulations and promulgating laws that support energy conservation. The European Union has introduced policies encouraging member states to adopt measures targeting energy conservation (Xu et al., 2017). In a similar move, the US has designated federal agencies for overseeing the conservation of

Table 6
Related works on feature engineering: Business, residential and policy.

Ref.	Methodology	Platform	Benefits	Drawbacks	User type	Feature
Nilashi et al. (2019)	Multi criteria collaborative filtering	Eco friendly hotel	Prediction scalability is able to handle large amount of user ratings	Effectiveness of proposed ANFIS requires further investigation	Consumers	Residential
Johansson and Thollander (2018)	Questionnaire & semi structure interviews	EMS	Efficient energy management	Proposed standard cater for long-term strategies	Industry, energy managers	Business & Policy
Hoicka and Parker (2017)	Interviews	EnerGuide for Houses and ecoEnergy programs	Results indicated positive response to complex retrofit model of residents	Lack of information on cost as a barrier to retrofitting actions	Homeowners	Residential

energy based on the United States National Energy Saving Policy Act of 1988 as amended. New Zealand energy strategy 2011–2021 specifies efficient use of energy as a major point in her four area of interest in the strategic drive towards energy conservation. Following this trend, a number of policy recommendations have been introduced by the Chinese government to promote energy efficiency and reduce GHG (Zhou et al., 2019). Work Zhou et al. (2019) reported that air pollution related to energy consumption is a major driver for policy reforms in the energy sector. Work Morton et al. (2018) presented Green Deal, a UK's Department of Energy and Climate Change initiative targeted towards energy efficiency policy for domestic energy and was implemented based on the following stages: Assessment of green deal using energy efficiency audit of appliances, recommendations provision based on cost effective energy options, and selection of green deal plan to mention but few. A similar measure is the information policies based on energy benchmarking and labeling (EU Energy Label and US lighting label) towards addressing information barrier by implementing ENERGY STAR across a number of EU member states and the US. Additionally, building codes and appliance standards are identified as important regulatory policy measures targeting energy conservation. Similarly, policy targeting consumer-oriented efficiency recommendations based on DT can encourage consumer to take up energy efficiency measures.

(b) Residential features: Energy efficiency in residential apartment is majorly associated with appliances and lighting, ventilation, heating, refrigeration and cooling (Moglia et al., 2018). Residential buildings currently account for roughly 40% energy consumption standing as the substantial consumption sector within the EU (Kompos et al., 2019) and measures required to obtain necessary features for accurate determination of residential energy consumption are required. In the same vein, energy waste in the residential sector is high due to a number of contributing factors. A major factor is low penetration of technologies that enable efficiency in the use of energy among consumers. Another is difficulty in quantifying and modeling the level of user comfort due to disparity among individual users making the deployment of automated building energy management units challenging (Shaikh et al., 2014). Having said these, the most important factor resulting in the misuse of energy in buildings is the issue of users careless behavior towards energy conservation. Researchers are identifying interesting approaches and features associated with recommendations based on the optimization of residential energy consumption. For example, real-time monitoring of residential energy consumption can contribute about 40% efficiency on the energy consumed in buildings (Kamilaris et al., 2014). Work Óscar García et al. (2017) presented an integrated approach using social computing and context aware platform for encouraging energy conservation among residents. Work Moglia et al. (2018) proposed adoption of resident energy efficiency using agent based model. In their work, recommendations for obtaining efficient energy products were provided to households using information agent. Work Hoicka and Parker (2017) proposed approaches for improving energy efficiency in homes using retrofit recommendations. They consider residential facilities as a system and indicated the potential for saving 50% to 80% energy if the specified retrofit stages are followed. They further identify high performance envelope such as wall insulation (make and model), and weather data as important retrofit feature for energy optimization (Hoicka and Parker, 2017).

(c) Business features: In recent years, the e-commerce industries have found wide use for recommendation system in the provision of personalized marketing experience to consumers (Guo et al., 2018). This aspect intends to provide information about relevant features associated with energy conservation in the business sector. Features falling into this category utilize data relating to businesses which could include nature of equipment, level of income, devices or machine that are deployed for production. Recommendations are generated using consumption profiles and consumers' action which can be in the form of heat produced by electric drives. The hospitality business is one out of many that has in recent times been responding to customers' sensitivity to the call for eco-friendly environment (Gupta et al., 2019). These calls have often resulted in hospitality businesses adopting energy saving and carbon reduction measures as part of their corporate social responsibilities (Lee and Brusilovsky, 2018; Nilashi et al., 2019). Work Nilashi et al. (2019) presented a multi criteria collaborative filtering technique for recommendation system based on preference learning of energy saving hotels. In their approach, preference on energy saving facility was predicted using Adaptive neuro-fuzzy inference system (ANFIS), while membership function of fuzzy logic was learned using ANN. A research was presented on e-commerce recommendation system for sustainable e-business using multi-source fusion of information (Guo et al., 2018). The author in Guo et al. (2018) employed the use of multi-source information to determine consumers preference for e-business recommendation system prescribing that an e-commerce recommender system should integrate features such as consumer location and historic behavior information (Guo et al., 2018). Work DixonoMara and Ryan (2018) examines the key motivation for introducing measures of efficiency in energy dependent sectors such as food retail sector. Paper Trianni et al. (2013) further identified features responsible for energy efficiency among different categories of consumers which includes business characteristics, operating environments, attitudes and reaction towards policies targeting energy efficiency. Similarly, International Energy Agency (2015) reported that developers of businesses can elect to pay attention to features representing the subset of an Small to medium-sized enterprise (SME), some of these include: the region of operation, size of the company, supply chain and the business sector.

These features are potential contributors to energy efficiency in SMEs. Other less tangible factors such as competition, disruption avoidance, consumer experience, and ambiance have also been identified (DECC (UK Department of Energy and Climate Change), 2014).

(d) Industrial energy-saving recommendation: For a low carbon economy to thrive, there is need for improvements in energy efficiency as 33% of the world energy consumption is a direct result of industrial activities. Improving energy efficiency at the industrial scale does not only have immense effect on the environment, but also lead to reduction of CE and the amount of GHG emitted while enhancing the competitiveness of the industry (Johansson and Thollander, 2018). By reducing the profile of a company's energy consumption, there is huge potential for improving profitability. Contrary to this, companies often fall short of adopting the several energy efficiency measures available, known as gap in energy efficiency (Jaffe and Stavins, 1994; Martin et al., 2012). Previous research works in this direction indicated great potentials for efficiency improvements in industrial energy consumption. A study on the driving forces and barriers associated with the uptake of energy efficiency in the industrial sectors and recommendations for energy management within homes has been presented (Johansson and Thollander, 2018). Work Trivedi and Bhatt (2018) provides a review on the application of energy conservation measures to the manufacturing industry. They reported that energy conservation is important as there are measures that enable conservation across manufacturing units. They further discussed technological measures that ensure energy conservation which resulted into recommendations of some actions that proposes to optimize energy in food, bread and metal industries. In a similar work presented by Arya et al. (2016) energy audit on aluminum industry was carried out by observing real-time, online and offline data resulting into 5 type of valuable recommendations for loads associated with: motors, lighting, fans and compressor. They further reported daily savings of 12 kWh by following recommendations applied to lighting load. Work Tan et al. (2019) reported on the implementation of energy substitution policy on industrial scale. They described 20 types of technologies aiding energy saving and emission reduction models which is further subdivided into 4 categories including electricity-, energy-, and coal-saving as well as the linkage technologies based on the energy saving effect of the itemized varieties of energy.

4.4. Social, economic and technical recommendations/tips

Consumer education is a conventional strategy for behavioral change on the execution of certain tasks. The behavioral control perception and the sense of consumer responsibility can be strengthened by providing them concrete and actionable suggestion. The provision of recommendations to consumers helps them to form the habit of energy conservation (Gölz and Hahnel, 2016; Koroleva et al., 2019). This section describes a number of recommendations/tips in the following categories: social, technical and economical recommendations.

(a) Social energy-saving activity recommendation: The concept of social computing encourages collaboration between machines and humans in providing solution to social problems based on the utilization of innovative socio-technical approach. This technique has evolved to become strong following the identification of agent's virtual organizations as a major powerful tool supporting social computing. By application, social machines are result of social computing producing entities that support social and technical management practices. An instance of such entities are social media platforms which include Facebook, Twitter, Instagram to mention but few. Social interaction resulting from the introduction of competition among consumers has proven to be useful tool in encouraging consumers to reduce energy consumption and further accelerate the change in behavior that favors energy conservation (Óscar García et al., 2017). In the same vein, social power gaming approach to conserving energy based on social interaction using real-time representation of cost, energy usage and data analytics has been examined (De Luca and Castri, 2014). This approach illustrates a friendly technique to achieve energy conservation using tools supporting energy visualization. In addition, social competition and feedback reward have been identified as viable measure for encouraging consumers to adopt energy conservation. This often appears in the form of collaboration, energy community or social competition (AlSkaif et al., 2018; Li et al., 2018b) allowing residential consumers to compare their energy consumption/energy performance to those of neighbors with identical household. To this end social computing paradigm can be implemented to develop a social system that allows collaboration between machine and human to resolve social related challenges using AI (Shadbolt, 2013). A number of social factors can be associated with acceptance of recommendations, thus advice or recommendation given by social peers or people belonging to trusted group are likely accepted (Starke et al., 2017). Work Luo et al. (2019) introduced an electricity retail plan recommender system for end consumer based on social information filtering techniques. Work Moglia et al. (2018) examined social network influence in the adoption of energy efficiency using agent based model for recommendation provision. Paper (Lee and Brusilovsky, 2018) presented a social link oriented recommender system that provides insight on related items. Work Óscar García et al. (2017) presented an integrated framework using social computing and context aware platform for encouraging energy conservation among residents. A concise summary of related review on social, technical and economic recommendations has been presented in Table 7.

(b) Economical energy-saving activity recommendation: The key role of implementing energy saving strategies lies directly on economic entities (Popkova et al., 2018). This therefore necessitates the need for economic entities to be interested in the process and results of energy conservation. According to UNEP (2011) annual report, for an economy to be green, it must display efficiency and fairness in terms of resources optimization, encourage social inclusiveness and must be low carbon based. Furthermore, the authors iterated on the importance of self motivation of economic entities in the developments of energy saving strategies. Issues associated with motivations for energy conservation for business consumers were discussed in Park and Kwon (2017). Work Popkova et al. (2018) reported on the approach for interpreting the importance of energy savings for the economic entities within the cooperate energy market using regression correlation analysis. The first considerations were given to self-motivation based on consumer or entities internal environment allowing organizations (entities) to identify energy saving opportunities using internal motivations and carrying out such implementations to facilitate energy efficiency. They identified the following requirements as necessary for achieving self motivation for energy saving (Park and Kwon, 2017):

- Provision of the logic and nature of the motivation process required for saving energy by the economic entity.
- Recognition of key variable required for energy saving motivation by economic entities.

Work (Campisi et al., 2018) presented on the economic viability of improving street lighting energy efficiency for residents of Rome. They discussed the economic implications of adopting LED luminaries technology and also computed the potential cost and quantity of energy it could save. Work Tetiana et al.

Table 7
Related works on social, technical and economical recommendations.

Ref.	Methodology	Platform	Benefits	Drawbacks	User type	Category
Óscar García et al. (2017)	Web monitor of the power application interface	–	Increased awareness about efficient use of energy based on social actions	Energy optimization was not maintained after the experiment was concluded	Public buildings	Soc
Koroleva et al. (2019)	Gamification approach, baseline and assessment questionnaires	Mobile app, Google fireball messaging service	Stability in energy consumption irrespective of exogenous factors	Short duration of study (4 months) may result into consumers relapse	Electricity consumers	Soc/Tech

(2018) developed an innovative model for replicating the economic behavior of agents associated with energy conservation. The authors developed a management system for introducing and analyzing energy conservation technologies. An approach based on the principle of economic efficiency was used to implement agent energy-conservation behavior model. Work (Hilorme et al., 2019) presented a model for forecasting entrepreneurship energy savings and further developed energy saving technologies for the identification of potential area for aggressive activities in the energy markets. By analyzing the developed energy saving models, conclusion was arrived at based on obtained economic efficiency. From economic point of view, Meshcheryakova et al. (2018) presented an article on the industrial facilities' energy efficiency and its role in societal development. The authors identified energy balance for a given production type and cost of production structure as a major indicator for the CE. They further provided recommendations targeted towards reduction in CE.

(c) Technical recommendations is a crucial part of measures geared towards improving energy efficiency. From the technical perspective of energy conservation, provision of stimulants and regulation towards utilization of the best available and efficient technologies and better energy auditing schemes to advance the cause of energy conservation is required (Alekseev et al., 2019). Recent research has also shown that consumer behavior is important factor for achieving efficient household energy conservation and technical intervention has been identified as a major enabler for achieving such efficiency in energy consumption (Alsalemi et al., 2019). Works that build on the use of technology for changing the behaviors of consumers in relation to energy conservation have been presented (Gaglia et al., 2019; Koroleva et al., 2019; Lester, 2015). Paper Gaglia et al. (2019) presented a technical and energy characteristics of residential energy consumption with the potential for energy conservation and emission reduction in non-insulated building. Their estimation of the percentage of various space heating for residential building type was obtained based on heating degree hour while potentials for energy conservation or estimation of occupancy behavior was determined using actual specific energy consumption. Furthermore, findings on considerations for the development of technological solutions to energy conservation problems have been limited in supply, and alternative approaches have employed theoretical models. None of the available approaches have been able to obtain a real-life validation of behavioral change favoring energy conservation or provide suitable recommendation in such manner for various categories of users. Similarly, the consumption of energy should be seen beyond individual decision but rather as an integration of technologies, social norms and infrastructures making it a social technical process. New directions are based on the use of machine learning models which categorize consumers by appropriately mapping them for personalized recommendation. An approach that integrates interactive visualization of consumption, attention triggers, recommendations for energy savings, smart meter data and gamification for socio-technical and behavioral changes for energy conservation measures was proposed by Koroleva et al. (2019).

5. Result analysis and discussion

This section gives an evaluation result of content analysis for summarized literature prevalent in the domain of discuss. In addition, the relevance of the selected papers was based on the subject of "innovation" and "energy services" (see Table 8) from selected databases. The relevance of selected documents was determined using keywords, citation index, and specific search categories in order to limit the wide scope of available literature. Owing to the heterogeneous and complex nature of IES, in all two major databases (IEEE Xplore and Scopus scientific library) were considered in this section and attention was given to categories such as "conferences" and "journals" with all presenting a point of view and unique contributions to the concept of IES. To better place the context (innovation, energy and services) and scope (IEEE Xplore and Scopus scientific library databases) to which this study is being conducted, we observed studies over a period of ten years starting from the year 2010 to 2019.

Energy services are categorized based on the nature of similarities or closeness. There is potential ambiguity in classifications as some services cuts across two or more categories. Services associated with water heating, space heating, cooling, lighting and cooking have been seen to be among the most occurring instance of energy services. Among the selected set of databases, key search words (Table 8) were used as query term to obtain the frequency of occurrences of the selected terms.

Fig. 4 is a pictorial depiction of results obtained from an objective evaluation of IES literature based on search result from IEEE Xplore and Scopus databases. It breaks down the frequency of occurrence of IES over the period between 2010 and 2019 by publication. It can be observed especially starting from the year 2013 to 2019 that IES enjoyed an upward trend across the two observed databases indicating about 83% increase in its adoption a result indicative of the general S-curve pattern of innovation services. In addition, the adoption of these services peaked in 2012 as observed across the two databases. This increasing trend can be associated with a number of factors which in most cases are social or economic factors and the possible adoption of innovations as a recovery mechanism from the 2008 global financial crisis. Such innovations are in the area of integration and improvements in performance of renewable energy sources (PV photovoltaic), integration of intelligent management of electrical network and increase in R&D spending on energy by the private sector. Such indication is the increase in private energy sector R&D spending which rose from 10.1 billion dollar in 2003 to about $21.6 billion in 2012 (Rhodes et al., 2014). There is also evidence that innovative activities and spending declined towards 2011 from 26.7% to about 10.8% during the period of crisis (OECD, 2012). Between year 2012 and 2013, content analysis revealed about 80% reduction in reporting IES. Across both databases, the situation analysis starting from 2013, indicated an upward trend in the adoption of IES.

Fig. 5 depicts the trend in yearly publications for IES contributing technologies. We used this trend to describe the historical

Table 8
Search keywords.

IES	DT	Recommendations	Behavioral attributes
“innovation” AND “energy services”	“energy services” AND “digital twins”	“energy services” AND “recommendation”	“energy services” AND “consumer behavior”

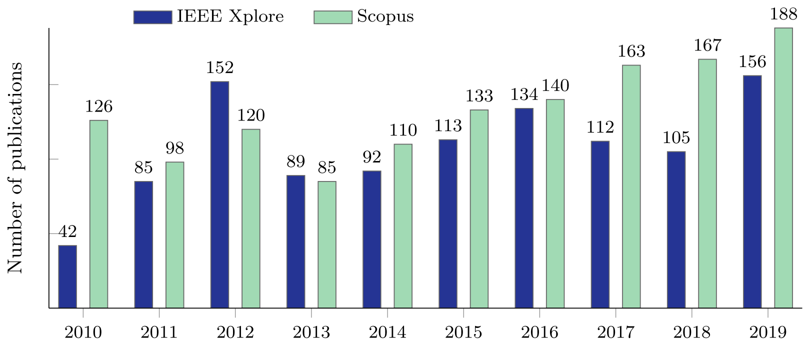

Fig. 4. Yearly number of publications in the period from 2010 to 2019 for IES from IEEE Xplore and Scopus database.

relationships between IES and individual contributing technologies. Trend indicates that behavioral reflective attributes closely follow recommendation tools, leaving DT with the least traction. This trends corroborates the possibilities of combining these closely related technologies. The slow traction recorded by DT publications can particularly be attributed to late introduction in the 2000s (Grieves, 2015), which however peaked in 2018. This dramatic increase in 2018 supports the conclusion that DT is one of top 10 technological trends in 2018 (Khajavi et al., 2019). Moreover, we visualize the percentage share of contributing technologies to IES (Fig. 5). A more significant increase was recorded by recommendation amounting to 53% which is closely followed by 45.3% recorded by behavioral attributes in the period between 2010 and 2019. This trend is plausible revelation that recommendation incentivized by extrinsic rewards is capable of stimulating pro-energy behaviors. To support this claim, a 0.911 correlation coefficient further corroborates a strong positive relationship.

When viewed through the lens of innovative studies, these trends can be seen to follow a classical path based on historical pattern of transition in technology where traditional notion of technology is threatened by advancement in innovation. Such advancements can be in the form of the introduction of smart meter technology, innovative contract offers, increase share of renewable energy, new business models based on peer to peer networking and informed customer participation in the energy market. An upward trend recorded from 2014 can be seen as positive sign of investments in R&D towards innovation in the energy sector which has been on the increase. Since 2015 a provision for an additional $4billion has been made available to about 40 initiated partnership in innovation and international research. These efforts are further reflected by the global measures by intergovernmental innovation initiative towards up scaling commitment for R&D investment into clean energy R&D between 2015–2020 (OECD, 2018).

It is worthy of note that overall outcome of the analysis indicated increase in the adoption of IES, subject to academic literature. However, occasional disagreement subject to the optimal approach to developing IES occurs in the energy industry (Greco et al., 2017; OECD, 2018). A way of viewing this is the long lead time existing between the research and development stage resulting in long payback periods experienced by private investors. In order to mitigate such effect, focused attention will be required from public sector to abate this effect with efforts in ensuring sustainable development in innovative solutions in the energy sector and provision of long term funding opportunities. This double prong approach will help cushion funding innovation while alleviating the effect of developmental gap and associated risks.

Challenges of proposed IES model: In spite the immense benefits associated with IES, there are often cases where effective adoption of these services by consumers are met with certain barriers or degree of failure. This can be subject to financial feasibility related concerns or lack of sufficient support from the government in the form of allocation for the IES uptake. Such could be as result of non-availability of energy audit report and necessary recommendation for improving energy efficiency based on adoption of IES. Again, in situations where necessary recommendations obtained from energy audit exist, advice given may have been considered as symbolic and never implemented. In some cases, local authorities set high targets which are often not practically feasible but majorly founded on political grounds of achieving their climate goals or gaining international political attention. Moreover, local authorities tend to lose focus on their initiating and refurbishing role towards implementation of IES, hence losing track or eventually detaching from successful implementation of such IES ambitions.

In other cases, deadlock often occurs resulting from poor experience with previous or similar IES projects, resulting to significant impact in the adoption of new or similar services by consumers. Behavioral barriers (Kowalska-Pyzalska, 2018) have also been suggested and can be attributed to bounded rationality such as lack of information, limitation in information processing capability, laziness or risk aversion preventing guaranteed rational behavior of consumers towards IES adoption as optimal choice. Integration of IES in some cases results into additional investments in infrastructure leading to increase in rent and are therefore considered as non profitable investment in the short term. Consumers are often weary of adopting IES even when the associated benefits are obviously presented to them, due to fears relating to potential teething problems normally associated with new technologies.

6. Conclusion

In this study, we presented a concept of IES based recommender system for personalized and smart advice provision based

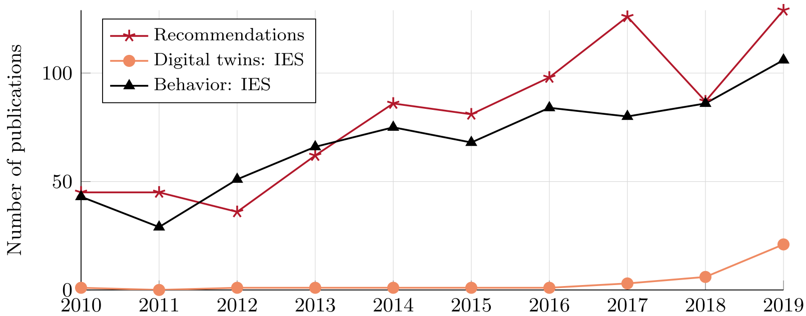

Fig. 5. Visualization of yearly number of publications for IES contributing technologies in the period 2010–2019 from IEEE Xplore and Scopus databases.

on holistic state-of-the-art review and content analysis of previous approaches. Our main contribution is to emphasize the role of consumers as major actor in the effort geared towards energy conservation by adopting innovative solutions provided by recent advances in recommender system and DT technology. The architecture of the proposed IES framework has been described in this study. The proposed platform provides energy saving options while alleviating the need to significantly alter consumers lifestyle. We observed two major trends in research. First, a comprehensive content analysis revealed an upward trend in the adoption of IES. This outcome supports the objectives of the study, indicating about 83% increase in its adoption. The second is the group of IES contributing technologies, content analysis revealed an upward trend recorded by recommendation studies produces identical outcome for behavioral attributes literature. This result further strengthens arguments that recommendation provision affects energy behavior. These research trends in our opinion are largely due to increase awareness, R&D investments, or various incentivized adoption of IES based DSM tools motivated by economic, social influence or psychological factors as suggested by literature.

Although the core investigation of the study is focused on the understanding of IES based on state-of-the-art review and content analysis of previous/antecedent approaches, one noticeable advantage is its applicability as stimulant or supporting information towards investments into consumer-oriented programs targeting energy efficiency. We acknowledge possible limitations relating to adoption barriers including teething problems identified with new or emerging technologies, behavioral barriers or poor experience with previous IES.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The work of A. E. Onile and E. Petlenkov was partly supported by the Estonian Research Council grant PRG658. The work of A. E. Onile in the project "ICT program" was supported by the European Union, Estonia through European Social Fund. R. Machlev and Y. Levron were partly supported by Israel Science Foundation grant No. 1227/18.

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Appendix 5

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A. E. Onile, J. Belikov, Y. Levron, and E. Petlenkov. Energy efficient behavior modeling for demand side recommender system in solar microgrid applications using multi-agent reinforcement learning model. *Sustainable Cities and Society*, 90:104392, 2023

Sustainable Cities and Society 90 (2023) 104392

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Energy efficient behavior modeling for demand side recommender system in solar microgrid applications using multi-agent reinforcement learning model

Abiodun E. Onile [a,*], Juri Belikov [a], Yoash Levron [b], Eduard Petlenkov [c]

[a] Department of Software Science, Tallinn University of Technology, Akadeemia tee 15a, 12618 Tallinn, Estonia
[b] The Andrew and Erna Viterbi Faculty of Electrical Engineering, Technion–Israel Institute of Technology, Haifa, 3200003, Israel
[c] Department of Computer Systems, Tallinn University of Technology, Akadeemia tee 15a, 12618 Tallinn, Estonia

ARTICLE INFO

Keywords:
Demand side recommender systems
Multi-agent reinforcement learning
Microgrid
Solar photovoltaic
BESS
Consumer comfort

ABSTRACT

Electricity consumers are often faced with challenges relating to the choice of an optimal energy saving plan. Increasing integration of transient renewable energy sources promises tantalizing solutions but also poses emerging stability challenges for the electricity grid. Demand side management using battery energy storage systems (BESSs) is crucial towards extending the physical limits of existing electricity grid. However, problems related to consumer behavior towards adoption of energy/battery efficiency measures and consumer comfort feedback exist. In this study, we present BESS technologies that are embedded into the grid and further enhanced with the use of reinforcement learning control and recommendation system technologies for improving the grid reliability, attaining self-consumption and demand response goals. The novelty of the proposed work is highlighted by using a separate class of active controller for BESS technologies, thereby separating it from loads which determine user comfort. Similarly, an adaptive demand side recommender scheme was used to provide recommendations targeting various microgrid entities. The result of the study shows that operating BESS using the multi-agent reinforcement learning control strategy achieved a maximum peak load reduction of about 24.5% alongside 94% comfort improvements in certain loads. The linear reduction in peak load was further enhanced by the BESS efficiency-related recommendations when compared to the baseline scenario.

1. Introduction

The energy system is a major physical infrastructure that supports modern human society. Traditionally, the energy system adopts the vertical integration structure with heavy reliance on non-renewable fossil fuels (Luo et al., 2016), which is fast depleting and encouraging an increase in energy prices. Consequently, this situation prevents a further expected exponential increase in the demand for energy (Kumari et al., 2021). A major contributor to this crisis is the problem of global population explosion, which has more than doubled since 1950 and has resulted in about a seven-fold increment in the demand for electricity energy. In a similar development, rapid growth in the magnitude of electricity demand in urban areas is introducing limitations in terms of constraints on the power lines, with consequences such as impending problems with the current electricity grid's needs for expansion or constant reinforcements (Vázquez-Canteli et al., 2019). By comparison to the present period, literature reveals that about 40 to 50% expected increments in consumption on a global scale with about 15% of water and global space heating is generated using electricity. For example, in the US, electricity consumption in buildings accounts for almost 70% of the overall electricity consumption (Vázquez-Canteli et al., 2019). Additionally, electricity usage for cooling in buildings within the OECD countries accounts for about 3.5 to 7% of the entire energy use in 2010. This is a trend that raises various energy conservation questions. Distributed generation technologies such as residential solar photovoltaic (or MGs) technologies are becoming more attractive due to promises of immense efficiency and their flexibility in operation, continuously falling system costs, less maintenance complexity, and ease of installation while proffering solutions to problems associated with emerging power consumption (Li et al., 2020).

Microgrid is an integration of various energy resources that is controlled by a sophisticated decision support system. Recent developments in microgrid involving renewable sources of energy such as solar have been seen as reliable electricity sources with significant potential for reduction in the emission of greenhouse gas (GHG) (Mengash & Brodsky, 2017) alongside promises of improved operation efficiency and flexibility (Li et al., 2020). However, islanded microgrids are often

* Corresponding author.
E-mail addresses: abiodun.onile@taltech.ee (A.E. Onile), juri.belikov@taltech.ee (J. Belikov), yoashl@ee.technion.ac.il (Y. Levron), eduard.petlenkov@taltech.ee (E. Petlenkov).

https://doi.org/10.1016/j.scs.2023.104392
Received 17 June 2022; Received in revised form 9 December 2022; Accepted 4 January 2023
Available online 13 January 2023

List of abbreviations

AI	Artificial intelligence
AMI	Advanced metering infrastructure
AMY	Actual meteorological year data
BEMS	Building energy management systems
BESS	Battery energy storage system
BTM	Battery thermal management
BTU	British thermal unit
CBR	Case based reasoning
CCI	Consumer comfort index
CFL	Compact fluorescent lamp
CSP	Curtailment service provider
DG	Dispatchable generator
DHW	Domestic hot water
DR	Demand response
DSM	Demand side management
dSOC	Discrete battery state of charge
DSS	Decision support system
EER	Energy efficiency ratio
EES	Electricity energy system
EMSs	Energy management systems
ESS	Energy storage system
EV	Electric vehicles
FCM	Fuzzy C-means
FIPA	Foundation for intelligent physical agent
GBDT	Gradient boosting decision tree
GHG	Greenhouse gas
HBESS	Home battery energy storage system
HVAC	Heating, ventilation and air conditioning
LED	Light emitting diode
MARL	Multi agent reinforcement learning
MARLISA	Multi-agent learning with iterative sequencing action
MDP	Markov decision process
MGs	Micrgrids
MLP	Multi-layer perceptron
NILM	Non intrusive load monitoring
nZEB	Net zero energy building
PDA	Personalized digital assistant
PMOIR	Power investment operation recommender
PMUs	Phasor measurement units
PR	Personalized recommender
PRS	Personalized recommender system
PV	Photo voltaic
RL	Reinforcement learning
RMSE	Root mean squared error
SAC	Soft actor critic
SG	Smart grid
SOC	State of charge
SVM	Support vector machine
TF-IDF	Term frequency-inverse document frequency
V2H	Vehicle to home
VAV	Variable air volume
VSM	Vector space model

susceptible to frequency and voltage instability, majorly because of low inertial and generating capacity (Ryan et al., 2021). As such, several issues still remain unsolved for a seamless deployment of microgrids to be achieved (Shuvo & Yilmaz, 2022). However, a possible solution to mitigate this challenge is the installation of additional spinning reserve (or grid reinforcement), which is often associated with additional cost and increased fuel consumption, greenhouse gas emissions, and a reduction in fossil-fuel generator efficiency (Ryan et al., 2021).

Battery energy storage systems (BESSs), on the other hand, promise significant help towards mitigating the stability issues associated with the microgrid by providing sufficient power reserve to mitigate the identified problems (Aghajani & Ghadimi, 2018; Ryan et al., 2021). In addition, BESSs play a major role in decarbonizing the grid by incorporating flexible RES and supporting demand response (DR) on MGs (Wang et al., 2018) while promoting operation flexibility and enhancing generation resource usage. From the power generation perspective, there is a need for sustained deployment of BESS and microcombustion for new power generation.

Such an increasing deployment of BESS poses a challenge which calls into question the problem of information filtering required to be faced by consumers. This problem is significant since an individual BESS possesses various operational configurations that consumers often lack the technical expertise to understand Guo et al. (2022). For example, grid-connected battery users or operators have a huge influence on the rate of battery degradation, and to increase sustainability, there is a need to improve battery lifetime (Eider & Berl, 2020). Inexperienced users lack the know-how for effective battery-friendly usage, and a comprehensive connotation of reduction in the lack of knowledge of inexperienced users through training and instruction may be required. Note that the degradation of batteries is dynamic and battery-friendly usage cannot be trivialized. As such, this challenge necessitated the need for an assistance tool that enhances the decision-making capabilities to help consumers on the microgrid achieve their energy efficiency goals.

Traditional DR expects consumers or managers to analyze various set-points and their impacts on various buildings in order to carry out DR on the microgrid. This is an extremely difficult task to accurately accomplish by a human operator. DR programs involve consumers' voluntary response to load curtailment or price signal requests by the curtailment service provider (CSP) or the utility (Behl et al., 2016). Consumers are, however, subjected to penalties if they under-perform or are unable to meet the specified curtailment level and receive financial reward upon meeting the specified level of load curtailment. Research revealed that various approaches targeting reduction in demand side electricity consumption using a range of methods such as heating, ventilation and air conditioning (HVAC), electronic devices, and lighting optimization (Wei et al., 2020) have been examined. A common problem, however, is that these efforts treat consumers as immovable objects by isolating them from the formulation of building optimization problems. This approach thus suffers some limitations associated with the amount or volume of energy reduction that can be achieved by passively optimizing around consumers, especially in cases where the majority of occupants' energy consumption in residential or commercial buildings is directly or indirectly used for providing services to occupants. Consumers require knowledge of the necessary set of actions that promote energy saving potential to effectively participate in energy optimization tasks (Wei et al., 2020). Work (Eider & Berl, 2020) has revealed that electricity energy consumers spend as little as two hours annually shopping for an appropriate electricity tariff. The study further revealed that consumers are reluctant towards dedicating or spending a significant amount of time on optimizing their home energy management, thus creating a need for automated management systems (US Department of Energy, 2008). *As such, the question is not whether consumers require advanced and innovative methods that help them achieve their energy goals while improving their comfort levels. The question, however, is how it can be achieved*?

Emerging technologies in the smart grid enhanced by the internet are generating an unprecedented volume of data obtained from widely deployed sensor units such as the Phasor Measurement Unit (PMUs), Advanced Measuring Infrastructure (AMI), Smart devices, etc. Luo et al. (2016). From the smart grid perspective, the explosion of data with rich statistical properties continuously streams from the demand side. Such big data collection could, on the one hand, pose a number of unparalleled challenges to utilities and system operators on how to adequately extract knowledge that can be useful for the optimization of grid operation, while on the other hand, the need for utilities to learn knowledge associated with data from the demand side (i.e., consumption patterns and behavior of consumers, output of distributed renewable sources of energy) is becoming increasingly important towards obtaining the knowledge for the design of optimal DSM programs (Luo et al., 2019). This technique incorporates continuous communications and feedbacks (Babar et al., 2020) between consumers and the grid using intelligent infrastructures, and thus allows them to make informed decisions relating to energy consumption, which is generally referred to as Demand Response (DR)/DSM (Logenthiran et al., 2012) and it is the major distinction between the traditional and the smart grid.

Personalized demand side recommendation systems (PRSs) are deployed to provide users with recommendations of different products and services by learning consumers' interests and preferences obtained via their historical data towards the provision of personalized energy efficiency services. PRSs are implemented with the intention of identifying items that would mostly interest the target user, which are not trivial tasks. In most cases, PR problems can be interchanged for problems related to predicting unknown users' interest values relating to an item. These values are regarded as ratings (Guo et al., 2022). Given the attribute of recommender techniques, their potential applications and impact in the smart grid domain are equivalently significant where the information of different participants of the grid needs to be filtered towards decisive decision-making requirements on diverse energy-related strategies or services (Luo et al., 2016) for providing actionable recommendations for energy-aware services or products.

From the BESS perspective, similar information filtering techniques show significant promise. For instance, to realize optimum BESS performance, it is required to implement a proper battery thermal management (BTM) scheme (Aciar et al., 2006). Such a system should be able to monitor and ensure safe battery storage system operating temperature whether it is operating within a safe temperature range while providing immediate feedback to consumers (in cases where there is no active cooling system) or to the systems' heating and cooling management module via a temperature control scheme (Hannan et al., 2020). Again, in the case of grid-connected batteries, energy market information can be used in controlling system charging information and sending control signals to the battery if energy price exceeds a certain threshold, the system sends a command to stop charging and start charging once the price falls back to a desirable level (Hannan et al., 2020). Additionally, the degradation of the battery is based on the historical perspective of the battery and current circumstances, as particular battery usage may be less optimal/battery-friendly for all situations. Hence, BESS users need decision support systems (DSS) such as predictive recommender systems (PRSs) that can help improve the quality of their decisions and support battery-friendly utilization, thus prolonging battery life (Eider & Berl, 2020).

Note-worthily, some actions place significant demands on consumers, as such some consumers may be unwilling to carry out specified energy savings tasks. Depending on the situation, some consumers are likely to shift their load during a peak hour while others may have responsibilities preventing them from shifting their energy use schedule (Wei et al., 2020). Consequently, there is a need for a correlation between an action's energy-saving potential and a consumer's willingness to carry out the proposed recommended action. In other cases, while recommendation provision significantly improves consumer energy behavior (Onile et al., 2021), some studies have advocated the introduction of a direct human feedback scheme for discomfort as an objective function that allows consumers to manually override recommendation and allow users' preference instead (Shuvo & Yilmaz, 2022). To achieve a high level of consumer comfort coupled with conservation goals, there is a need to equip consumers by exploiting new techniques for controlling user-side loads on the micro-grid.

In this paper, the consumer-end energy recommendation model has been developed with a default multi-agent RL control model architecture for eliminating elements of discomfort. Comfort constraint was achieved in multi-agent RL by placing the assumption that the action of the controller does not influence the indoor temperature or the building's active thermal mass and, as such, does not actually change the energy consumption of the building, with the exception of the active storage system. This therefore allows the cooling and heating demand of the house to be satisfied at all times irrespective of the actions of the reinforcement learning controller, which are automatically overridden to satisfy the comfort constraint and thermal energy demand and allows the controller to exclusively focus on shaping the demand curve without running the risk of obstructing consumers' comfort (Vazquez-Canteli et al., 2020). The proposed framework (described in Fig. 1) consists of demand side recommender and RL-based control modules that enable effective user-side load control. The research objective of the study is to design and implement a demand side recommendation framework for solar microgrid applications using a multi-agent reinforcement learning model. At the core of the framework is a content-based filtering of recommender system that compares the microgrid entities such as behavior of consumers/BESS to their prior behavior/profiles so as to propose value-added services to consumers for the purpose of demand reduction and efficient operation of the BESS in microgrid scenarios.

2. Literature review

From the review perspective, traditionally, research into energy storage systems for residential applications has paid attention to BESS and photo-voltaic (PV) generation, see Table 1. Recent works have considered the optimization of operations and size of the integrated BESS-PV system with the aim of maximizing PV self-consumption and minimizing cost. For instance, a number of studies have paid attention to the hybrid PV+BESS operating strategies coupled with feed in limits. An example is the case of tariffs used to limit the amount of PV generation meant to be fed-back into the power grid normally associated with Germany (Olivieri & McConky, 2020). Another key finding submitted by a similar study has shown that incorporating demand and PV production forecasts into the strategies of operation while setting limits for state of charge can significantly improve battery life compared to the traditional approach of simply targeting self-consumption maximization (Hesse et al., 2017). However, a common challenge with these control practices is that consumers are likely to ignore price/tariffs signals, as previous research shows that price signals may not necessarily influence changes in energy behavior in cases where users consider it as discomforting (Torriti, 2012). This shows limitations in cost-associated feedback, a better approach is the use of recommendation systems that engage consumers with targeted feedback rather than cost-based control schemes.

A substantial number of studies based on non-intrusive smart grid recommender models have also been examined (Luo et al., 2016; Mengash & Brodsky, 2017). Work (Mengash & Brodsky, 2017) investigates the application of recommendation systems for smart grid demand side management (DSM). A service recommendation for a smart grid demand side management (DSM) application with emphasis on the technologies and the vision of the smart grid is proposed in Luo et al. (2016). Consumer appliances' utilization features were extracted using NILM techniques. Another study on a recommendation model using social information collaborative filtering-based electricity retail plan in a smart grid application has been published by Luo et al. (2019). The proposed collaborative filtering smart grid residential end-user's recommendation system technique was implemented using cosine-similarities and fuzzy C-means (FCM) clustering. These studies suffer from potential

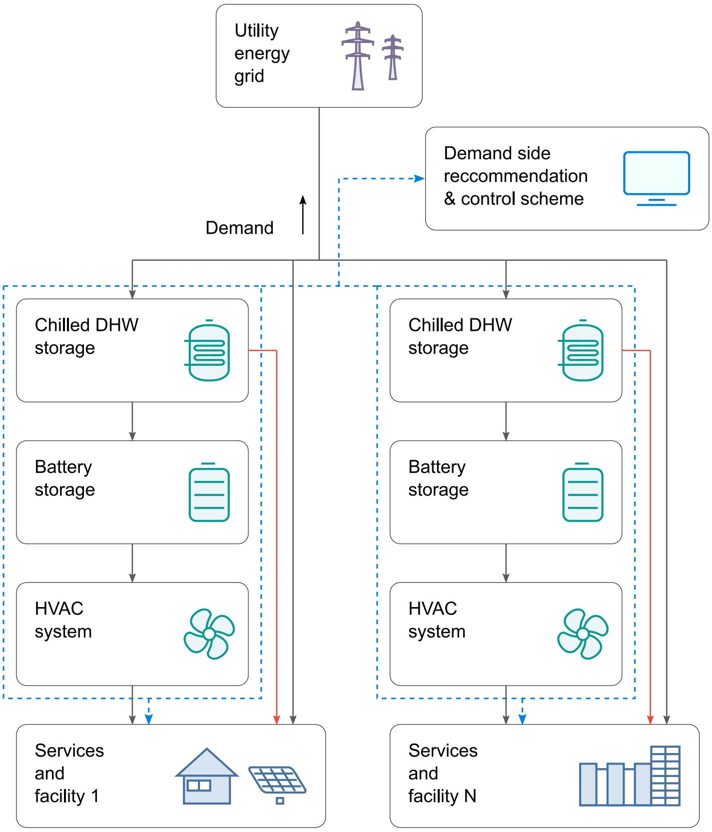


Fig. 1. Overall scheme of proposed solar microgrid based demand side recommendation and multi-agent reinforcement learning control framework.

limitations, which include data sparsity and cold start problems. Again, the solution targets consumer information from a retail perspective, which can heavily constrain behavior computation from a microgrid perspective.

Work (Ohno & Suzumura, 2021) presented a study on battery electrolyte recommender systems using ensemble Bayesian optimization. Study outcomes show significant potential for obtaining solution-mixing rules for maximizing ionic conductivity. Similarly, the proposed model records significantly better performance compared to the random search approach. Although, in relation to this study, further studies are required to determine whether observation influences the effect (positive or negative) of ensemble. As another example, the authors in Dunlop and Farhi (2001), Eider and Berl (2020) and Luo et al. (2016) have presented personalized recommender to achieve an extended lifetime of batteries connected to the grid. Work (Eider & Berl, 2020) presented a prescriptive recommender system requirements for achieving an extended lifetime of EV batteries. The proposed model implements decision support systems' functionalities that extend EV and electric system lifetime by providing recommendations on battery-friendly EV operation, such as usage advice and current or upcoming situations. The study, however, noted that future work will be required for model implementation and testing in a real-world application. Work (Klör et al., 2017) presented a report on the application of the recommender system for value-added service for repurposed EV batteries using item-based collaborative filtering. In the study presented by Liu et al. (2021) an EV based battery recommendation was examined. The author in Zeynali et al. (2021) described that application of plug-in EV battery energy storage system (BESS) based demand response program (DRP). The result is impressive, albeit it is less adaptive with a focus solely on the MG BESS entity. Note-worthily, the majority of works focused on EV applications and, as such, with limited scope.

Similar works focusing on operations and investment optimization in DR (Barker et al., 2012; O'Shaughnessy et al., 2018) recommendation applications were published. However, these approaches also only focused on specific components or on a single criterion (i.e., cost, consumption reduction, etc.). Similarly, the majority of these systems focus on single users and are not designed for handling scenarios involving a group of entities (i.e., BESS, end consumers) such as microgrid systems (Nottrott et al., 2013). Although other recent works have also proposed recommendation applications capable of aggregating consumers' individual preferences towards achieving a group model (Hittinger & Azevedo, 2015). On the other hand, the majority of these grouped recommender systems have been designed for atomic services rather than adaptively accommodating packages of services or products. Additionally, most of the recommender systems depend solely on a single utility or ranking score, which falls short of many applications that need to take their multicriteria nature into account, as can be seen in microgrid scenarios (Olivieri & McConky, 2020).

Beyond the aforementioned studies, which are mainly focused on singular entities (i.e., end consumers or EV-BESS) for smart-grid recommendation models, a number of studies have also focused on the application of categorical energy service recommendation systems in standalone PV applications. Another work on service recommendation methods for energy service recommendations has been presented (Wu

Table 1
At-a-glance overview of works on demand reduction controllers and recommender systems using BESS.

Ref.	Focus	Contribution	Methodology	Limitation
Guo et al. (2022)	Personalized recommender system for HBESS selection	Eliminates cold-start problems by obtaining not rated consumers preferences	Neural collaborative filtering technique, Neural network	Non end-consumer applications
Ferreira et al. (2011)	HBESS products recommendations	Maximization of driving route information	Personal Data Assistant (PDA); Android SDK	Full integration challenges
Hannan et al. (2020)	Investment recommender for RES	Recommender model for microgrid operation & Investment	Mixed integer linear programming	Scaling problems with increasing RES components
Kumari et al. (2021)	Prosumer recommender	Securely P2P blockchain, real-time smart contract recommendation	Reinforcement learning	less platform adaptive
Kaur et al. (2019)	Multi-agent BESS-PV & light recommender	Recommends optimized energy consumption for users comfort	Java Agent, MATLAB	Solely for lighting/less scalable
Ohno and Suzumura (2021)	BESS electrolyte recommendation	Significantly maximizes BESS ionic conductivity solution mixing rule	Ensemble Bayesian optimization	Additional studies are needed
Mengash and Brodsky (2017)	RES microgrid operation and investment recommender	Supports optimization for group of user	Mixed-integer linear programming	Less robust model
Wei et al. (2020)	Building management system	Scalable model for cooperative DSM	Deep reinforcement learning	User discomfort due to relocation needs
Pinto et al. (2019)	Intelligent energy management in buildings	Case-based reasoning recommender system	Support vector machines (SVM), k-nearest neighbor clustering algorithm	Requirements for historic data
Klör et al. (2017)	Electric vehicle batteries value-added recommender	Value-added re-purposing recommendation services	Item-based filtering	Cold-start problem
Luo et al. (2019)	Demand side energy management systems	Adaptive to group of users	Collaborative filtering, cosine-similarities, Fuzzy C-means clustering	Cold-start problem
Shuvo and Yilmaz (2022)	Home energy recommendation system	Human feedback and activity data based objective function	Deep reinforcement learning	Choice of relevant data for MDP model

et al., 2020). The study analyses various categories of integrated energy services using a collaborative filtering model based on neighborhood towards the presentation of a new set of integrated energy services classifications.

Paper (Luo et al., 2016) presented a study on personalized recommender systems for home BESS using neural collaborative filtering, general matrix factorization, and multi-layer perceptron (MLP). The proposed model recommends suitable HBESS from numerous potential BESS products. Case studies show that the proposed system was capable of effectively obtaining trends in users' preferences and presenting users with recommendations that were previously not rated by users. As such, it eliminates the cold-start problems in personalized recommender systems. Another study that attempts to close the gap between individuals on the micro-gird towards achieving group efficiency recommender system has been presented (Mengash & Brodsky, 2017). The authors presented the application of a group recommender system for power investment operation recommender (PMOIR) for microgrid renewable energy sources using a mixed integer linear programming model. Although these studies achieved significant energy conservation results, consumers are likely to face occasional discomfort or ignore recommendation/energy saving tips to avoid such possible discomfort (Shuvo & Yilmaz, 2022).

In recent research, efficient control schemes targeted at BESS-PV group level consumers' energy behavior based on a multi-agent RL control model have been presented (Shuvo & Yilmaz, 2022). Work (Wei et al., 2020) presented a recommender system for optimizing energy consumption in commercial buildings based on an occupancy-driven approach using a deep-reinforcement learning model. The outcome of the study shows about a 19%–26% reduction in energy consumption using a novel building energy optimization problem formulation, based on a scalable model for cooperative energy conservation. Work (Darwazeh et al., 2022) presented an overview on the implications of demand response strategies deployment for indoor environment while providing recommendations targeting peak load reduction and improvements in user's comfort feedback (Fratean & Dobra, 2021). Another important work on the application of deep reinforcement learning models for home energy recommender systems using consumer activity and feedback has been published (Shuvo & Yilmaz, 2022). The proposed model study incorporates human feedback into the DSM objective function. The presented RL state definition was enhanced using human activity data for energy optimization performance. A significant study outcome of the proposed model shows an immense capacity for adaptiveness to a broad spectrum of different resident profiles and homes.

Despite the rich literature targeting the implementation of recommendation/control schemes for the optimization of BESS-PV models and end-user energy profiles (see Table 1), a very limited number of studies have paid attention to the ensemble of these three uniquely important aspects: user-side recommendation, multi-agent RL control, hybrid PV-BESS scheme towards DSM optimization and end-user comfort. Even though some studies have been presented on the application of recommendation systems to DR applications, which are mostly independent from works targeting BESS optimization and DR applications with end-user comfort constraints. A synergy of these independent technologies holds significant benefits for the desire to achieve a truly non-intrusive, consumer-focused and comfortable DR solution. Therefore, a research gap has been identified, especially in relation to the comfort constraint of consumers in responding to DR recommendation signals in an end-user focused energy efficiency scheme.

This study thus identifies a gap which begs the question: Whether adding a user-end recommendation scheme sufficiently achieves a comfortable and consumer-focused DR? There is a need for the development of an efficient, consumer-focused method for power management and control for BESS-PV microgrid application. By identifying the essential functionalities of the consumer-centered decision support system (DSS) for micro grid hybrid BESS-PV from literature, it is possible to derive generic requirements that a PRS needs to satisfy. Subsequently, these requirements are discussed from the perspective of consumer comfort constraints using multi-agent based RL control based design for implementation there by closing the identified gap.

2.1. Contribution

In this paper, we have not only targeted the consumers' behavior and comfort improvements but also the performance of the BESS for overall optimization of grid operation. The present research can be summarized as follows: A novel and adaptive demand side recommendation system based on hybrid BESS for PV integrated DR has been developed to capture the interdisciplinary characteristics of BESS physical/internal chemistry and consumer behavior. Specifically, the proposed reinforcement control model while prioritizing utilization of hybrid PV generated and energy storage in place of the grid, and improvement of battery efficiency while achieving a reduction in peak generation and demand, aimed at increasing potentials for self-sufficiency and PV self-consumption in buildings. Hence, compared to previous studies, this paper contributes in the following areas:

1. Presents a novel concept of adaptive demand side recommendation system based on hybrid PV-BESS and multi-agent reinforcement control scheme optimized for improvement in degree of user's comfort, battery efficiency, and reduction in net electricity consumption in a microgrid scenario. Specifically, the proposed multi-agent reinforcement control model ensures comfort by actively controlling the BESS and prioritizing utilization of hybrid PV generation and energy storage in place of the grid, thus increasing the potential for PV self-consumption in buildings and achieving a reduction in peak consumption. For comfort constraints, it avoids passive control of comfort loads, which is left within the purview of non-intrusive recommendation/control scheme. Consumers comfort constraints is determined with consumer comfort index (CCI) metrics (see Section 3.5).
2. We have presented and discussed the application of BESS technologies based on the provision of advice targeting the optimal operation condition of a battery storage scheme by the utilization of energy storage recommendation technologies towards attaining prolonged battery life and the sustainable and reliable provision of energy by extension.
3. Presents a model-free multi-agent Reinforcement Learning (RL) control algorithm for obtaining load control using grid-coupled BESS with values ranging between 1kWh and 30kWh capacity for peak shaving applications. We further demonstrated the applicability of the proposed model using a set of buildings and a user study performed towards the measurement of real energy savings for a simulation period of 12 months.
4. We present a feature formulation technique for extracting electricity from a multi-dimensional transition matrix built on a graph-based ranking model for scoring consumer energy behavior patterns for the provision of personalized, consumer-focused, and actionable recommendations towards improving the microgrid's occupants' energy efficiency.
5. We demonstrated the generalizability potential of the proposed model to adapt to different weather conditions and applied it to a number of household consumption profiles using an open-sourced AI gym testbed for learning different classes of energy-efficiency recommendations for microgrid operators. The models were validated/evaluated based on their ability to reduce net peak demand, net annual demand, total ramping, daily average peak, average daily load factor maximization, and minimization of user discomfort on the microgrid.

From the foregoing, a common situation for microgrid consumers is to want to address the problem of increasing electricity demand/cost, an objective function which does not improve linearly with end-users' comfort. This dilemma can be resolved via a synergy of the technologies that offer better potential for future demand side recommender model for consumer-focused solutions. As such, this study aims to present a conceptual model for meeting the specific integration requirements of PV-BESS, electricity consumer intelligent recommender systems and multi-agent RL control for DR purposes. The research objective of this study is to demonstrate the design and implementation of adaptive DR recommendation model based on various interdependent models that were previously considered disjoint (i.e., PV, BESS, recommender system, multi-agent RL, etc.) with consideration to consumer comfort constraints. The core of the model (see Fig. 1) comprises an item-based collaborative filtering recommendation system for comparing the performance of BESS and consumers with historic optimal performance. Based on the measured index, the framework presents consumers and decision-makers with value-added advice/recommendations for DR optimization problem.

The remaining aspects of the paper are structured as follows. Section 3 contains the background of the study. Section 4 describes the proposed methodology for the BESS-based reinforcement learning control framework and recommendation system. The numerical result and evaluation of the model are described in Sections 5 and 6. The conclusion of the study is presented in Section 7.

3. Background

3.1. Microgrid and energy system

A microgrid system is an integrated framework comprising of energy resources alongside the sophisticated decision support system (DSS) required to control them. It is a smart energy network capable of operating independently from the bulk generation using independent distributed energy resources. An example includes the power microgrid of an industrial facility, building complexes or even a university campus (see Fig. 1) (Mengash & Brodsky, 2017). DSM has been identified as an important aspect of the smart or microgrid which allows consumers to optimize their energy consumption (Nasir et al., 2021).

3.2. Demand side management in microgrids

Demand side management techniques are categorized generally into indirect load control (pricing-based DSM approach) and direct load control (incentive-based DSM approach) (Luo et al., 2019). The incentive-based DSM approach allows energy utilities to effect direct control on residential energy resources such as home appliances and EV using remote control for reshaping the energy load profiles with the aim of providing support to before meter applications or applications at the grid-level, some of which include voltage/frequency regulation, peak load reduction, etc. Consumers are often provided with rewards or incentives by the utility as a means of subsidy. Pricing-based DSM programs allow utilities to set the price of electricity signal towards stimulating electricity demand from consumers, achieving active adjustment of consumers' appliance utilization or effect load demand reshaping while optimizing the operation of the grid. For instance, price difference stimulation helps users adjust their electrical appliances for consumption to a time with a valley load period rather than the peak load period and thus achieves a reduction in peak load on the grid (Luo et al., 2019). Recent efforts are being geared towards the transformation of utility services into ecommerce-based in order to provide services to end consumers in ways that are more convenient (Luo et al., 2019).

3.3. Energy storage technologies

Energy storage systems (ESS) have gained wide consideration for the provision of affordable, reliable, and sustainable energy supply on the grid alongside its wide acceptance and deployment in developed economies such as the USA, Australia, Spain, Japan, China, etc. This technology can be broadly categorized into six major categories based on either their method of usage or construction, while each category relating to electricity storage technologies can further be classified based on their applications into: pumped hydro energy storage technology, electro-chemical storage, electro-mechanical storage, electrical storage, chemical storage, and thermal storage. Most countries with an interest in affordable, sustainable, safe, and secure energy sources have adopted available battery technologies options that are fully utilizable and available to them in their energy sector. The global share of the utilization of each storage technology by different countries has been considered in Naseem et al. (2018). Battery capacity depends on some operational factors, which include discharge rate, battery age, temperature, and depth-of-discharge (Dunlop & Farhi, 2001). Notably, battery availability can be significantly impeded due to high charge rates, lower operating temperatures, and limited depth of discharge. Work (Naseem et al., 2018) presented a description of the various set-points for optimal control required during the various battery technologies' charging regimes (i.e., at 25 °C, flooded lead antimony and flooded lead calcium charges at 14.4–14.8 and 14.0–14.4 V, respectively). Energy demands increase only during operational hours, allowing the majority of commercial and industrial consumers to experience constant operation. In this case, the battery is charged during the non-peak hours and utilized during the operational hours, thereby significantly reducing peak demand charges. Generally, energy storage allows the storage from embedded generation units to be stored and retrieved at peak times. On a global scale, the forecast shows that the market share for BESS demand is evenly split between front of meter and behind the meter applications, while the behind the meter market is further divided between commercial and residential consumers (McCarthy et al., 2019). Notably, there are cost and benefit implications associated with these emerging markets for both electricity consumers and network operators, which require further understanding. Amongst the many opportunities that are obtainable from the deployment of 'behind the meter' commercial scale BESS, a major area includes demand peak and its associated cost reduction for commercial electricity consumers (Zhou et al., 2021).

3.4. Recommendation system

Recommendation systems have found significant application for decision support aids, particularly in e-commerce applications. This provides consumers with recommendations capable of enabling them to deal with tasks involving preferential, multi-attribute or multivariate choices (Keeney et al., 1979). Recommendation systems can be broadly classified based on the techniques applied, such as content-based filtering, collaborative filtering, and hybrid model (Adomavicius & Tuzhilin, 2005). Additionally, some less common classifications include the knowledge-based, utility-based, and demographic recommender system (Klör et al., 2017).

Collaborative filtering-based recommender systems use the preferences expressed by other consumers for certain products. Based on the belief that consumers that have common preferences for certain products are likely to share similar preferences for other products (Ekstrand et al., 2011). As such, products liked by neighbors (identical consumers) are suggested or recommended. Again, for collaborative filtering, the similarity between users is based solely on preferences for a product and not on any particular property of the product. These properties can be expressed either based on previous purchases (implicitly) or by ratings (explicitly) (Bobadilla et al., 2013). User-to-user or user-based collaborative filtering has been faced with scalability problems as the consumer base grows, (Ekstrand et al., 2011). A common variation of this problem is found in item-based or item-to-item collaborative filtering that simply replaces consumers with items, enabling similarities precomputation (Ekstrand et al., 2011). A common problem with both of the mentioned approaches is the "cold-start problem" (Bobadilla et al., 2013) when the available amount of user or item contextual information such as ratings and historical purchases is not sufficient.

Contrary to this, a content-based approach is less susceptible to missing data and instead uses descriptions of the properties associated with provided items/products to generate additional data. As such, any possibility of such a disadvantage refers to the description of items provided, which are normally available for recommendations and can reveal inherent similarities existing between products. Tags and standardized keywords are normally used to describe items (Adomavicius & Tuzhilin, 2005). Users' preferences are normally used to recommend items and can be expressed directly by users or indirectly as a derivative of previous behaviors (e.g., historic transactions). Hybrid recommender systems are hybrid derivatives of content-based filtering and collaborative filtering recommender models (Klör et al., 2017).

Energy service recommendation method: The introduction of internet technology allows integrated energy services to be transacted using integrated energy services platforms. It is important at the same time to obtain an analysis of potential consumer needs for an integrated energy service company towards the development of an effective integrated energy services framework capable of encouraging increased consumer participation. Thus, service recommendation is becoming an important functional element of a future integrated energy service system or platform.

Catalogue of integrated energy recommendation services: A comprehensive catalogue of energy services presented in this study includes three service menu items (BAT_R, EFF_R, and REC) which were established as connoted in the following paragraph. The three menu items can be further categorized into services such as comprehensive efficiency improvements; renewable energy and storage; energy engineering and trading; electrical equipment and smart home; and electrical energy substitution (Wu et al., 2020)

- BAT_R: BESS for renewable recommendation;
- EFF_R: Efficiency improvement recommendation;
- REC: Energy efficiency recommendation for electrical equipment.

Each service connotation described above is introduced as follows (see implementations in Table 9). The BESS and renewable energy recommendation service (BAT_R) includes recommendation provision for energy storage appliances, photovoltaic, electric vehicles, and renewable and distributed energy resources. The energy storage appliances comprise of batteries for power applications and mobile energy storage (i.e., for EV and construction power supply), etc. Photovoltaic applications incorporate the use of photovoltaic modules and panels. Furthermore, two additional categories, which include energy efficiency (EFF_R) and load management (REC) were considered (York et al., 2007). As such, the recommendation catalogue (EFF_R) for efficiency improvement recommendation main structure comprises of specific tips and energy solutions targeting improvement in energy savings; energy efficiency products and services recommendations; strategic conservation programs; electric energy substitution services targeting comprehensive improvements in energy efficiency. Lastly, (REC) falls into another broad category targeting end-users with energy-management/cost saving, energy-efficient electrical installation and operational efficiency improvement recommendations.

3.5. End-user comfort index

One of the key objectives of the proposed model is to achieve a reduction in peak demand and, as such, minimize energy costs. However, another important aspect to consider is the end-users' comfort, especially in relation to efficiency recommendations dealing with certain types of load (i.e., comfort load/devices). For example, loads such as compressors, ceiling fans, water pumps, lamps, etc. can be considered as comfort loads for the users. As such, users' dissatisfaction level can be increased by effecting recommendations for shifting or scheduling such loads. In order to achieve a reduction in the level of users' dissatisfaction, this study uses hybrid solar PV-BESS alongside a multi-agent RL control scheme to actively control the BESS system while excluding the comfort loads to the purview of consumers, thereby increasing consumer comfort/satisfaction level (Tamilarasu et al., 2021). In this study, this metric is denoted as consumer comfort index (CCI) which is the ratio of the number of hours without service due to end-user recommendation to the total number of hours a device is put into service.

4. Methodology: material and methods

In this section, various techniques involved in the development of the proposed model were introduced. First, the methodologies presented utilize the architecture described in Fig. 1. Major feasible elements incorporated include the use of multi-agent RL control (MARLISA) scheme while also utilizing the implementation of non intrusive recommendation scheme (i.e., rating prediction) to jointly achieve a consumer-centric and comfort based demand side management model, while minimizing user dissatisfaction. Again, the proposed scheme involves the use of methods optimized for aggregation of switchable (shiftable) loads while extracting the behavior of load and BESS system (Dickie, 2016). This research thus presented a consumer-focused model that implements the described adaptive recommendation scheme in a hybrid PV-BESS microgrid and RL control for demand response. The vertical integrated model cuts across individual components of the framework towards the presentation of the core functionalities of proposed framework. In our attempt to develop the prescribed model, we reviewed various literature contributing to consumer-focused demand side recommender systems and improving operational efficiency/re-purposing batteries for stationary grid applications that resulted in a number of optimal design principles/elements (i.e., three such as R_BESS, REC, and EFF_R). Moreover, the prototyped model was iteratively developed in Python, OpenAI Gym Environment (Vázquez-Canteli et al., 2019) and the application of PageRank scoring model for recommendation provision.

4.1. Data-driven demand response and behavior forecasting

Weather prediction: The forecast accuracy of solar irradiation is based on forecast error characterization, which can be defined as the difference between the measured and predicted energy irradiation for a specific period of time. Predicted weather data is required to be generated based on the modification of actual delivered PV profiles depending on the error distribution function discussed in Lödl et al. (2011) in order to be used in the simulation model. The PV feed-in model is, therefore, segmented into days attributed with high, medium, and low values of irradiation. The hourly average PV feed-in values are afterwards used to obtain the equivalent distribution function errors. The daily average generation is obtained using the integration of a simulated daily PV delivery forecast. We adopted the prediction of weather data and consumption profiles to determine changes in the behavior of consumers and BESS operations on the microgrid. Owing to the fact that the study involves a significant amount of simulation, some forecasting data is based on simulation data as well. This corresponding data was generated within the simulation framework.

End-user load forecast: The prediction and forecasting of consumers' load profiles is also required to be predicted towards the operational optimization of home PV storage systems. A simplified prediction equivalent of consumer load profiles p is used considering the difficulties involved in accurately forecasting their load profiles for the next few days. Based on this assumption, the predicted consumer load profile is p is divided into the following parts: sunrise to sunset, midnight to sunrise, and sunset to sunrise. The daily electricity consumption accrued within the specified period of time t is computed and averaged for a simulation period of a month selected from 120 h experiment simulation window (Zeh & Witzmann, 2014), see Fig. 3.

Forecasting with *Machine learning* predicts the responses to recorded data. In this study, changes in consumers' energy behavior were predicted using an autoregressive model. Although such an approach is simple, it produces powerful results. Such models require less computational power in terms of running time and requirements for storage. Autoregressive model represents a given type of randomness and can be useful in defining time-varying processes such as in the end-user's energy profile. The outputs of the autoregressive model depend linearly on previous values and stochastic terms, as such it can be presented as a stochastic difference equation. Prediction with AR for a signal X_t can be achieved using a combination of it past weighted values $X_{t-1}, X_{t-2}, \dots, X_{t-p}$ (Abdullateef et al., 2012). As such, $AR(p)$ notation depicts the autoregression model, which can be defined as:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon. \tag{1}$$

Again, $AR(p)$ denotes the autoregression model of the order p, and ε is the white noise. The model parameter is represented as φ_i and c is a constant.

4.2. Consumer behavior modeling for recommendation provision

Rating consumer behavior profile: The problem was approached by using a graph-based analysis for the description of consumer behavior. In general, consumer behavior can be modeled using consumer energy transition frequency (Onile et al., 2021). A time-varying flow that plays a significant role for behavior graph topology evolution (rise and fall of edges and nodes) in order to achieve a description of the end-user energy profile. Link prediction constitutes a significant study problem in the area of network evolution because it helps in the prediction of links that will evolve in the future. Ranking of consumer energy consumption can be done based on the prediction/analysis of load dwell time, which can be used to alert consumers about the identification of frequently occurring load levels. Historic/forecast data was collected for the establishment or extraction of a rating matrix as

$$G_{ij} = \begin{array}{c} \text{load-}C_r \\ b \\ m \\ p \end{array} \begin{array}{c} \begin{array}{ccc} b & m & p \end{array} \\ \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{bmatrix} \end{array}. \tag{2}$$

Each row in the rating matrix represents the user, while each column describes an item (battery, load profile, etc.). Variable load-C_r is the load criteria which includes base (b), peak (p), and mid (m) load profiles, while r_{ij} is the actual rating obtained from the jth user correlated with item i. The rating value is associated within a range r_{ij} (0,1), where a higher value is a representation of high consumer preference (Wu et al., 2020). The described graph-based PageRank algorithm can be used to predict consumer or node transition behavior (Onile et al., 2021). As such, we define the behavior model as a ranking problem, which can be shown as follows (Dickie, 2016): Let $G = (V, E)$ such that V is a set of nodes and E represents a set of edges or links. The behavior attempts to find the cheapest consumption points while also identifying/scoring the highest consumption (Lee et al., 2012). In general, consumers with a history of longer consumption profiles can have higher scores. Each score is not treated or considered to be equal with another score in a different load profile or load-C_r (i.e., base, peak, and mid load) when used for recommendation provision.

We obtained transition frequencies from the original consumption profiles of consumers as well as the predicted profiles, which were converted into scores. The Graph-based ranking (PageRank described in (5)) model was considered as a preference in computing the scores following its superior performance in the outcome of our study in Onile et al. (2021). The present study utilizes a ranking model based on a number of multidimensional matrices required for optimizing the consumption behavior and storage performance in a microgrid system. These matrices include historic and ambient temperature; historic consumption; and the transition frequency/probability associated with the flexible loads were all considered for computing the ranking scores. The recommendation mechanism is configured for the selection of flexible loads with higher scores based on the application of historic data, and we selected a graph-based PageRanking algorithm for obtaining scores or ranking of raw data (Tao, 2016) following the application of TF-IDF for data vectorization in the recommendation provision. Term frequency-inverse document frequency (TF-IDF) was used to obtain the TF-IDF matrix or Vector Space Model (VSM) from a consumer's energy profile. The vector's components represent the importance of certain load categories or their absence in certain load profiles. TF-IDF allows vector representation of textual data as

$$\text{TF-IDF} = \text{TF}(t, d) \cdot \text{IDF}, \tag{3}$$

where

$$\text{IDF} = \frac{1+n}{1+df(d,t)} + 1. \tag{4}$$

Here, IDF represents the inverse document frequency and TF is the term frequency, t is the term contained in document d, and n is the number of data points/profiles that were considered in a given simulation window. More elaborately, $\text{TF}(t, d)$ represents the raw count/frequencies of term t in document d. PageRank can be defined as

$$\text{PR}(V_i) = (1-d) + d \sum_{i=1}^{N} \frac{\text{PR}(v_i)}{N(V_i)}, \tag{5}$$

where d is the damping factor, N is the total number of nodes, and $\text{PR}(v_i)$ is the currently ranked consumption profile.

4.3. Recommendation system

The study considers the application of a content filtering recommender system for the provision of DR recommendations for microgrid operations (Zheng et al., 2020). Furthermore, the recommendation method for integrated microgrid energy service adopts a recommendation model based on ranking or scoring consumer energy and battery profiles targeted for recommendation provision. The following paragraphs describe the flow of implementation. First, we implemented the recommendation segment based on the scores obtained from the graph-based PageRank algorithm since it scales properly with a smaller amount of data and does not require initial training. Another key advantage of this algorithm is its potential to outperform similar graph-based ranking models as described in this study (Onile et al., 2021). As such various recommendation tips from the pool of advice targeting DR and battery optimization were able to effectively match the needs of consumers compared to traditional control scenario (Onile et al., 2020). Following the calculation of the degree of similarities between target consumer, in addition to obtaining an aggregate of the users' preferences, the target users' predicted rating on different consumption plans are determined and sorted in a descending order of the ratings predicted (top-N), where the top N efficiency tips are recommended to the consumers. This recommendation is obtained for each target consumer from the analysis of the electricity consumption pattern that has a similar profile to his/hers while suggesting the pricing plan, or efficiency measure that is most suitable to the target consumer (Luo et al., 2019). The algorithm for implementation of the recommendation system for flexible load is described in Algorithm 1 adopted from Tao (2016).

Algorithm 1 Recommendation of Integrated microgrid load/BESS for downward load ramping.

1: **Input**
2: Historical lists (set L), $L_1, L_2, \ldots, L_m$ of flexible loads
3: Temperature lists (set T_B), $T_1, T_2, \ldots, T_m$ of BESS
4: **Output**
5: Recommendations of all flexible loads
6: Recommendations of optimal charging voltage

7: Recommend all loads if dispatch order is larger than size of all flexible loads and charging voltage is within acceptable temperature margin and go to 8
8: Compute space separation TF-IDF between B_l, M_l, and P_l using (3)
9: **for** $k \leftarrow 1$ to Total_number_of_FlexibleLoads **do**
10: Remove list exceeding B_l
11: Remove list exceeding M_l
12: Remove list exceeding P_l
13: **end for**
14: **for** $k \leftarrow 1$ to Total_number_of_FlexibleLoads **do**
15: Compute scores obtain from ranking model using (5)
16: **end for**
17: **for** $k \leftarrow 1$ to Total_number_of_BESS **do**
18: Compute the optimal charging voltage associated with current ambient temperature
19: **end for**
20: Sort top-N flexible load based on ranking or scores
21: Recommend flexible loads with the highest rank score until dispatch order is accomplished
22: Recommend update battery charge voltage
23: Construct and update new list Set B_l, M_l, and P_l; and Set T_B

4.4. Demand response reinforcement learning control scheme

The control scheme was developed using a simulation platform for demand response based on Reinforcement learning (RL) agents implemented in OpenAI Gym Environments available on the GitHub repository (Vázquez-Canteli et al., 2021). Data associated with heating and cooling loads was loaded from either building or surrogate models. Controllable energy supply and storage modules such as batteries, thermal energy storage, and air-to-water heat pumps were implemented within the OpenAI Gym framework. Building heating and cooling loads were also modeled using OpenAI Gym Environments (Vázquez-Canteli et al., 2019), which is a microgrid scale building energy simulator. This simulator uses a physical reduced order and geometric 3D models for estimating the building's heating and cooling loads. The model further accounts for internal heat gain consequent to solar irradiation, thermal losses, and occupant activities. Buildings were modeled as a single-thermal zone that accounts for energy storage and different devices for cooling and heating supply. RL adopts a model-free and agent-based control model that is capable of learning based on its interaction with the environment it intends to control and can be defined using a Markov decision process (MDP) that is comprised of a set of state S, action A in addition to the transition probabilities for moving between states $P : S \times A \times S \in [0, 1]$ as

$$V^{\Pi}(S) = \sum \Pi(S, a) \sum \text{P}^{a}_{ss'} \left[\text{R}^{a}_{ss'} + \gamma V^{\Pi}(S')\right]. \tag{6}$$

The agent in its goal attempts to maximize discounted reward's expected cumulative sum within an infinite time horizon.

We begin by defining the major components of the DR problem in order to develop the control framework. Following the description

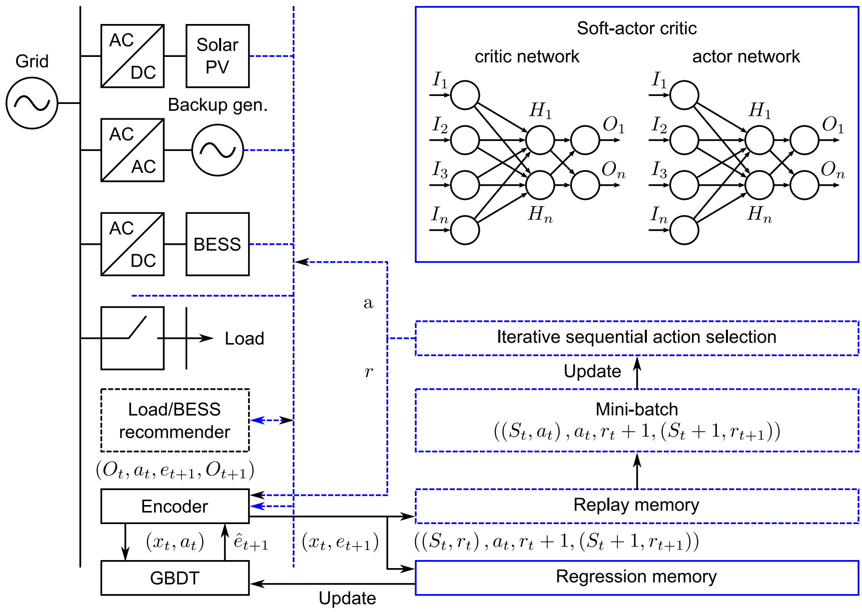


Fig. 2. Simulation framework for MARLISA model in end-consumer energy-BESS recommender scheme based on microgrid network's key components.

given in Fig. 2, the various components represent the electricity load or energy demand, energy supply systems, and the BESS that are connected to the grid. Following the integration of physical models, RL agents are used for coordination of the storage devices and energy supply based on fluctuations in energy prices. Using a bottom-up structural approach, microgrid entities such as supply devices and BESS sit at the bottom, constituting the class of simplest objects attributed to this environment, instantiated and controlled by the building class. On the top of this in the hierarchy is the simulation, which inherits attributes and methods of the super class in OpenAI Gym Environment. The RL-based demand response simulation environment was experimented using nine buildings, with each building deployed with an individual RL agent based on MARLISA. The buildings were able to learn by interacting with each other in order to minimize the cost of electricity energy demand and achieve a flattened overall electricity demand curve on a microgrid. Fig. 2 illustrates the reinforcement learning agent for demand response environment.

Given that $R^{a}_{ss'}$ represents $r(s,a)$ which is the reward obtained following an action $a = \Pi(sk)$ resulting in transition from the current to the next state $s \rightarrow s'$. Policy p maps the states with actions, while $V^{\Pi}(S)$ represents the agent's expected return if it follows policy p and starts from state s. The future rewards obtained from the discount factor are given by $\gamma \in (0,1)$. It is important to note that the transition probabilities (environment dynamics) of model-free reinforcement learning models are often unknown. An example of a commonly used model-free reinforcement learning technique is Q-learning. Transition probabilities can be represented using a table that contains Q-values (the stat-action values) in tasks that contain small state sets. Every entry in the table contains a state–action tuple (s,a) while the update of the Q-values can be represented as

$$Q\left(S_t, a_t\right) \leftarrow \left(S_t, a_t\right) + \alpha\left[r\left(S_t, a_t\right) + \gamma max_a Q(S_{t+1}, a_t) - Q(S_t, a_t)\right], \tag{7}$$

where $\alpha \in (0,1)$ represents the learning rate that determines the degree to which new knowledge updates old knowledge and s' is the next state. Following each action taken under a certain state, Q-values are the representatives of the expected cumulative sum of discounted rewards based on greedy policy. Q-learning performs updates to its policies based on past experience using off-policy methods and might have obtained such experience using different policies. In furtherance to this, Q-learning is an off-policy approach that is capable of performing policy updates independent of its currently adopted policy by depending on past experience that was probably collected by means of a different policy. The state–action-reward tuples are fetched from the replay buffer where they are stored in order to carryout iterative updates based on (7). The RL model utilizes the Q-learning approach that is trained and tuned to reduce the cost function (Chen et al., 2018).

Q-Learning agent design. State and Action. The microgrid state is determined by the battery SOC and the balance of power. The state space continuous measures are discretized based on a different range of variables as shown in Algorithm 2. The following describes the discrete state space ranges as discrete state of battery charge (dSOC) (Kofinas et al., 2016). The *Reward* is based on a number of factors, which include the battery state of charge (SOC), and the power demand coverage. Power supply coverage is achieved when the supply of power to load is about 80% of the overall power demand. The goal is intended to maintain the battery SOC maximum value while at the same time trying to cover the amount of energy demand in a situation where the battery SOC is below the maximum value. The reward termed as battery SOC (r_{SOC}) can be described as follows (Kofinas et al., 2016):

$$r_{SOC} = \begin{cases} 1 & \text{SOC} > 90\% \\ -1 & \text{SOC} < 20\% \\ 0.1.soc_d t & 20\% \le \text{SOC} \le 90\% \end{cases} \tag{8}$$

given that $soc_d t$ represents the deviation in the rate of SOC obtained at consecutive different time slots. Again, the SOC is continuous in nature, but the state space has been descritized using different ranges such as

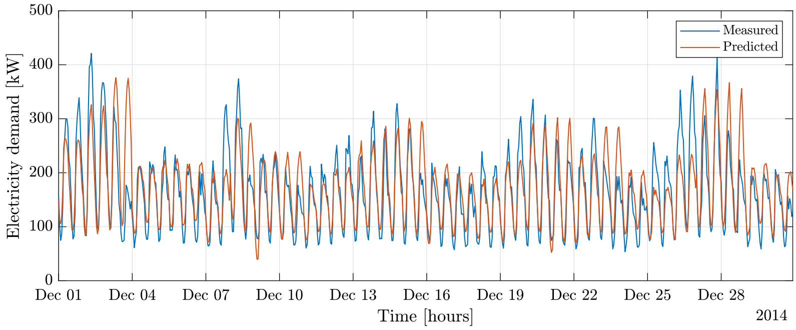


Fig. 3. One month in advance, predicted vs. actual electricity consumption towards consumer behavior scoring using the Forecaster Autoregression model.

1, 2, 3, and 4 for the sake of this study; as such, the discrete state of battery charge (dSOC) is given as follows (Kofinas et al., 2016):

$$\text{dSOC} = \begin{cases} 1, & \text{if } 0\% \le \text{SOC} < 25\%, \\ 2, & \text{if } 25\% \le \text{SOC} < 50\%, \\ 3, & \text{if } 50\% \le \text{SOC} < 75\%, \\ 4, & \text{if } 75\% \le \text{SOC} < 100\%. \end{cases} \tag{9}$$

4.5. Reinforcement learning based on soft-actor critics approach

In order to control an environment that incorporates continuous actions and states, it is impractical to use a tabular Q-learning due to its tendency to suffer from the curse of dimensionality. The actor-critic RL approach, on the other hand, uses artificial neural networks for achieving generalization across state–action space where the current state is mapped to actions that are estimated as optimal by the actor network. Furthermore, estimated actions are evaluated by the critic network by mapping them alongside the states to Q-values. Soft actor-critic (SAC) is an example of an off-policy model free RL model (Haarnoja et al., 2018) that is capable of reusing experience that was learnt from a few examples. SAC model is built on three major elements, which include: actor critical architecture, entropy maximization for training stability and efficient exploration, and off-policy updates. The model is capable of learning three individual functions: the value function V in (10); the soft Q-function (critic); and policy (the actor) (Vazquez-Canteli et al., 2020):

$$\begin{aligned} V(S_t) &= E_{at\sim\pi_\theta}\left[Q\left(S_t,a_t\right) - \alpha \log\theta\left(a_t|S_t\right)\right] \\ &= E_{at\sim\pi_\theta}\left[Q\left(S_t,a_t\right)\right] + \alpha E a_t \sim_\pi \theta[\log\theta\left(a_t|S_t\right)] \\ &= E_{at\sim\theta_\pi}\left[Q\left(S_t,a_t\right)\right] + \alpha H, \end{aligned} \tag{10}$$

where $H \geq 0$ represents the Shannon entropy for policy π_θ, which represents the allowable action that can be taken by agents' probability distribution under a given state S_t and $\mathbb{E}_{at}$ is the expectation term. A deterministic policy $\pi_\theta = 0$ for every action outside the optimal action a_t^*, such that $\pi_\theta(a_t^*|S_t) = 1$ can be represented with a zero entropy. More randomized action selection is allowed for policies with a non-zero entropies. SAC agents' objective includes learning of optimal stochastic policy π^* represented by

$$\pi^* = \arg\max \sum_{t=0}^{T} E(S_t,a_t) \sim \rho_\pi\left[r(S_t,a_t) + \alpha H(\pi_\theta(\bullet|S_t))\right]. \tag{11}$$

Simply by selecting the policy's (mean distribution) expected action as the choice action, the final optimal policy can be deterministic, which is a required ingredient for evaluation of the agent after training is conducted. Given that $(S_t,a_t) \sim \rho_\pi$ represents a state–action pair obtained from an agent's policy, $r(S_t,a_t)$ represents the reward associated with a given state-agent action pair. As a result of the addition of the term representing entropy, the agent tries to maximize the returns while maintaining possible random behavior. By minimizing expected error J_Q between the calculated and predicted Q-values (using iteration), parameters representing critic networks are updated.

$$\begin{aligned} J_Q = E\left(S_t,a_t\right) \sim D\Big[\frac{1}{2}(Q_Q(S_t,a_t) - (r(S_t,a_t)) \\ +\gamma E S_{t+1} \sim p\left[\mathrm{V}_Q^-(S_{t+1}))^2\right]\Big]. \end{aligned} \tag{12}$$

The temperature represented as $\alpha \in (0,1)$ in Windham and Treado (2016) is a hyperparameter that must not be confused for the learning rate in Leibowicz et al. (2018). This parameter controls the entropy term importance and, as such, allowing the stochastics of learned $\alpha = 1$ to prioritize maintaining maximum potential for stochastic behavior that is capable of resulting in uniformly random behavior, while allowing $\alpha = 0$ ignores entropy in its entirety, with only agent focus on return maximization while excluding the need for exploration, resulting in a policy that is almost deterministic. In this study, this value has been set to a constant value of $\alpha = 0.2$ (Vázquez-Canteli et al., 2019).

4.6. Multi-agent reinforcement learning with iterative sequencing action (MARLISA)

This subsection of the methodology discusses the application of the multi-agent reinforcement learning model and its utilization in the control of BESS with study outcome comparison and evaluation based on a multi-year case study. MARLISA is an extension of the soft-actor critic (SAC) algorithm (Nweye et al., 2022) (described in Section 4.5) that facilitates the coordination of agents using reward sharing along with mutual information sharing in a manner that is decentralized, scalable and anonymous (see details in Fig. 2). Each agent is required to share two variables, which ensure the scalability of the algorithm in order to achieve coordination (Vazquez-Canteli et al., 2020). This is due to the condition that the number of variables required by each agent does not increase with the number of agents. As such, MARLISA model can be useful in the decentralization of multi-agent problems, as is the case with coordinated load shaping in a microgrid system. MARLISA model was implemented in the microgrid framework for controlling chilled water and DHW storage (Vazquez-Canteli et al., 2020; Vázquez-Canteli et al., 2019). The RL agents transmit a set of control actions (on an hourly basis) while a set of rewards and state s is received in return. The indoor temperature is kept constant by following the environment's automatic constraints of controller actions while guaranteeing large enough energy supply devices to maintain a constant energy supply to buildings. At any given time, the RL decides the quantity of heating or cooling energy storage or supply required. The microgrid framework's integrated backup controller ensures that energy supply devices guarantee buildings' energy demand satisfaction prior to proceeding to store additional energy. In the implementation of the MARLISA (see Fig. 2) model, every house within the microgrid is equipped with an individual RL agent with a design objective that allows individual agents to learn to coordinate among each other whenever they are initialized using a random policy and with a lack of system dynamics knowledge. From an energy perspective, agents should be capable of learning to shape the microgrid overall load profile. In particular, the agents were evaluated based on their ability to reduce net peak demand, net annual demand, total ramping, daily average peak, average daily load factor maximization, and minimization of user dissatisfaction on the microgrid. Some parameter of multi-agent model used includes a learning rate of $lr = 3 \times 10^{-4}$, batch size = 256, decay rate $t = 5 \times 10^{-3}$, ydiscount = 0.99, and neural network architecture with 256 × 256 hidden layer size.

To integrate MARLISA we utilized the Huber loss, which is less prone to effects produced by outliers, along with the use of layer normalization applied to all critic networks layers due to its tendencies for speeding up network training. Principal component analysis (PCA) was applied to achieve a 25% reduction in the dimensionality of the encoded observation. Reward design for the experiment was done using various reward structures (see (13)). Single target rewards such as r_i^1, r_i^2, and r_i^3 are considered due to the fact that their values primarily depend on the value of agent/building i net electricity consumption e_i. When the building consumes more electricity than the amount generated $e_i < 0$, while $e_i > 0$ if the building generates excess electricity at this time and is thus self-sufficient. The partially collective MARLISA RL agents' reward functions based on combination of individual net electricity e_i utilized and its collective component $\sum e_i$ is defined as

$$r_i^{MARL} = -\text{sign}(e_i)e_i^2 \min\left(0, \sum_{i=0}^{N} e_i\right). \tag{13}$$

For instance, this is the overall electricity consumption of residents on a microgrid that helps to share information among agents and therefore rewards them for achieving a reduction in the coordinated energy demand. The empirical results described in Vázquez-Canteli et al. (2019) report that an excellent result was produced by using an exponential of 2 for e_i and exponential of 1 for the collective factor $\sum e_i$. The mean and standard deviation were calculated at the beginning of the simulation at the start of the random exploration phase following the collection of all rewards, which was followed by collected reward normalization alongside potential future rewards. As described in Vazquez-Canteli et al. (2020) the sign of r_i^{MARL} changes based on the values of collective and individual factors. When the building is consuming electricity from the grid, the rewards become negative while the microgrid is also dependent on the grid for electricity consumption. However, rewards are positive when more electricity is generated by the building than what it is consuming from the grid. This is due to the fact that the building is contributing to the energy self-sufficiency of the micro-grid system. When there is no electricity supply from the grid and the micro-grid is self-sufficient, all the agents receive a zero reward.

The use of collective rewards, previously described above, makes a provision for the actual and more accurate goal description of the micro-grid for each agent. This approach, however, increases the level of reward stochasticity as each agent's states are unable to explain the changes associated with the collective reward factor. In order to remedy this problem, an approach that shares some information among the agents that is sufficient for them to make an accurate prediction of the outlook of the next reward under the current state if certain actions are taken is considered. Each rewards r_i^{MARL} received by individual agents depends on both individual net electricity consumption and the demand attributed to the entire micro-grid system. As such, a gradient boosting decision tree (GBDT) model is trained for individual buildings based on agents' actions and a normalized subset of observation O_i for the prediction of building net electricity consumption at the following time step once a given course of action is followed.

A description of the GBDT model at mth step will fit decision tree $h_m(x)$ to the intermediate error terms given as difference between intermediate predicted and actual value (Pseudo residuals). The decision tree $h_m(x)$ for all input x is written as sum as follows (Friedman, 2001)

$$h_m(x) = \sum_{j=1}^{j_m} b_{jm} 1 R_{jm}(x), \tag{14}$$

where j_m denotes the number of leaves. The input space is partitioned by the tree partitions into j_m distinct regions $R_{1m}, \dots, R_{jm}m$ while predicting a given value at each region. Again, coefficient b_{jm} represents the prediction value in the region of R_{jm}. To minimize loss function, γ_m is chosen by line search and further multiplied by coefficient b_{jm}. By discarding the coefficient b_{jm}, and choosing a separate optimal value of γ_{jm} in-place of a single γ_m for the entire tree, the model is updated as

$$\begin{aligned} F_m(x) &= F_{m-1}(x) + \sum_{j=1}^{J_m} \gamma_{jm} 1 R_m(x), \\ \gamma_{jm} &= \arg\min \sum_{x_i \in R_{jm}}^{n} L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)). \end{aligned} \tag{15}$$

In summary, iterative sequencing action selection (Vazquez-Canteli et al., 2020) was achieved when a list of agents that has been randomly sorted is created each time an action selection function is called. The action a_{ik} is picked by the first agent on the list, and its GBDT algorithm predicts, e_{kl} the quantity of electricity the building will consume following the consideration of the picked action e_{kl}, and further shares the information with the next agent. Actions are kept on hold and are not taken individually at this stage. A collective action A is finally taken which is the set of all the agents actions.

Algorithm 2 Q-Learning

```
Initialise Q(s, a) table
for each episode do
    Initialise s
    for each step of episode do
        Based on policy derived from Q(ϵ − greedy) choose a from s
        Take action a, observe r, s′
        Take action a, observe r, s′
        Q(s, a) ← (1 − α)Q(s, a) + α [r + γ_max Q(s′, a′)]
        s ← s′
    end for
end for
```

Algorithm 2 depicts the Q-learning in reinforcement learning algorithm for the control of flexible loads and BESSs (Kumari et al., 2021).

4.7. Simulated scenarios (details)

The case study is carried out by taking the OpenAI Gym energy simulation platform, which is operated for microgrid energy simulation scenarios as an example. As mentioned above, there are 10 occupants per unit in first level directories (an apartment) and a total of 9 second-level directories (buildings). In the case study, the neighbors are established based on the data of the second-level directory, and the recommendation is accurate up until the bottom-level directory. We simulated about 20 active users on the simulation platform to establish the sample set of devices (controllable and non-controllable). So, based on information obtained from Table 2, the project rating matrix has 3 rows and 3 columns (base, medium, and peak load) depicting a discrete form of Fig. 4. The 20 active user loads cut across controllable and non-controllable installed devices, for residential customers and industry zone customers (Wu et al., 2020) (see Table 2).

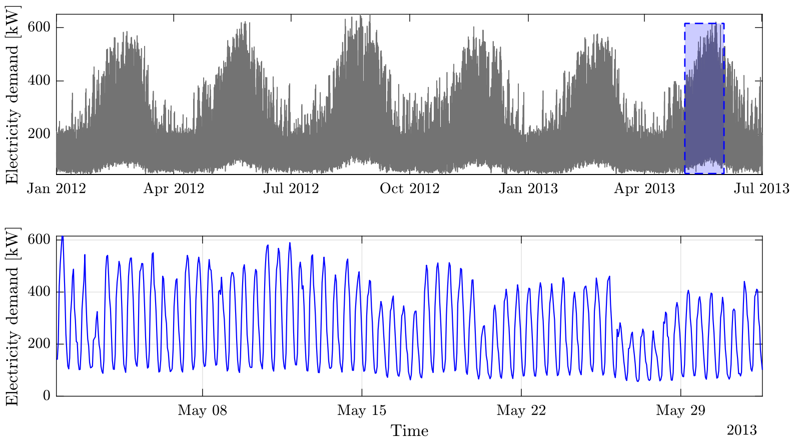


Fig. 4. Original consumption profile without the application of BESS for a period of 120 simulation hours. Top plot full resolution; bottom plot zoomed in sample of the graph.

Table 2
Load profile of selected end-user devices for 24 h simulation period.

Considered appliances	Sampling time per hour	Taxonomy (Sharda et al., 2021)	Energy (kWh)
Computer	8(11am, ...,13pm)	Uncontrollable	1.5
Notepad	3(11am, ...,13pm)	Irregular scheduling	0.01
Electric stove	6(7am, ...,11am; 18pm)	Nondeferrable	4.5
Power shower	1.5(8am; 19pm)	Nondeferrable	7.5
Hair blower	1(8am)	Essential	3
Dishwasher	1(20pm)	Deferrable	2
Light	8(1am, ...,5am; 20, ...,24pm)	Fixed	3
Fan	3(1am, ...,3am)	Fixed	0.06
HVAC	24(1am, ...,24pm)	Regulate-able	3.8
Refrigerator	24(1am, ...,24pm)	Hard load	2.5
Vacuum cleaner	3(6pm, ...,8pm; 17pm)	Irregular scheduling	1.5
Space heater	16(1am, ...,11am; 20pm, ...,24pm)	Delay tolerant-flexible	1.8
Central AC	7(12pm, ...,18pm)	Regulatable	6.7
EV	5(22pm, ...,3am)	Battery assisted	10
Washing machine	5(1am, ...,2am; 21pm, ...,24pm)	Reschedulable	2.2
Cloth dryer	3(1am, ...,2am; 21pm)	Non-flexible deferrable	4
CRT TV	3(10am; 14pm; 18pm)	General appliance	0.5

The building under consideration was simulated in the EnergyPlus virtual test-bed. The virtual test-bed occupants reside in the building during peak hours and are equipped with two electric water-cooled chillers, a gas-based boiler, and a variable air volume (VAV) supply air terminal containing plum and reheat zones. At peak load, about 486.5 kW power can be consumed by the building. EnergyPlus provides typical simulation meteorological data attributed to many sites, generated as an average of different weather for a period between 15–30 years. For the purpose of simulation, actual meteorological year (AMY) data was utilized obtained ranging between the years 2012 and 2013. Pecan Street dataset obtained between 2013 and 2016, with the option for open sourced energy consumption datasets provides the data basis for our methodologies. Load consumption profile and weather data was also obtained from Pecan street database (Pecan Street Inc. Dataport, 2022; PecanStreet Dataport, 2017).

4.8. Evaluation metrics/framework

We adopted the use of the following evaluation metrics in the experiments, which include: Root Mean Squared Error (RMSE) (for identifying behavioral changes), Cost Benefit Analysis, Social Cost of Carbon Estimation, and Consumer Comfort Index (CCI). Relating to data, baselines was used to denote a basis for comparison against various model that were experimented. The baseline was the original consumption profile of the smart grid consumer alongside the profile associated with the SAC control scheme. Again, we used the model described in the microgrid SAC control scheme in order to determine our baseline controller. We compared the baseline with the proposed MARLISA method suggested by the framework using the described evaluation metrics. Furthermore, a method was adopted for the evaluation of the method's success rate in relation to end-users' comfort. Experimental results were evaluated from the perspective of the following parameters: Olivieri and McConky (2020) and Tamilarasu et al. (2021): (i) Battery's charge state and temperature, (ii) Social cost of carbon, (iii) Cost benefit analysis, (iv) RMSE, and (v) Consumer comfort index.

Root Mean Squared Error is a method that can be adopted for measuring errors associated with a model in numerical information scenarios, and is defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(p_i - q_i\right)^2}, \tag{16}$$

where N represents the complete training set, p_i is the deliberate information estimation, and the actual consumption value is q_i. RMSE thus estimates the performance of the prediction. The consumer comfort index is given as

$$\mathrm{CCI} = \frac{\text{Number of non-recommended hours of operation}}{\text{Total number of hours of period of operation}} \times 100. \tag{17}$$

5. Numerical results and analysis

In this section, the results of the experiments are discussed. This comprises the result of the recommender system and the outcomes

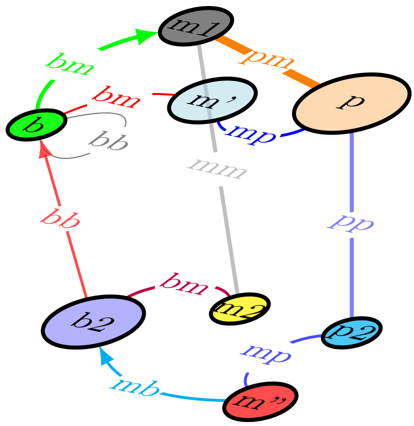


Fig. 5. Sample transition graph of consumption profile between base (b), mid (m), and peak (p) load for a 48-hour simulation period.

of multi-agent RL control signal for achieving flatten load profile following implementation of the proposed framework. Similar effects are expected for the optimization of battery performance following the recommendations of battery optimization tips targeting the BESS.

5.1. Rank and recommendation

Fig. 3 describes a month-ahead prediction or forecast of end-user electricity profile using regression analysis described in Eq. (1), and consumption profile obtained from the bottom plot in Fig. 4.

The top plot in Fig. 4 depicts the full resolution of the original consumption profile without the application of BESS while the bottom plot is the zoomed resolution for a simulation period of 120 h intended for load prediction. This forecast in Fig. 3 allows for the a priori understanding of whether the behavior of consumers is likely to change or worsen within the projected window, thus allowing for timely intervention or the provision of advice/recommendation for reversing such a trend. These changes in behavior can be seen, for example, with a computed Root Mean Squared Error (RMSE) of 274.317 between the predicted and real consumption profile. This predicted trend is further descritized into three main load transition/frequency categories, which include the base, mid and peak load which can be fed into the transition matrix described in (2) to obtain a set of scores shown in Table 3. Additionally, the descritized trend was useful in obtaining the transition graph, see Fig. 5.

Table 3 describes the ranking scores for multidimensional flexible load profiles towards downward ramping (Tao, 2016). Ranking scores in Table 3 represent the rank outcome of the graph-based scoring model for the predicted and actual consumption profiles. In each case, the result shows that the load profile 1 (representing base load) was much lower than the load profile 2 (representing mid load). When compared to load profile 3 and load profile 4, the results further showed that the effect of the control structure has significantly reduced the score of the peak load as a result of the peak shaving outcome of the RL based control. Tables 8 3 describes the various ranking scores for multidimensional flexible load profiles towards downward ramping (Tao, 2016).

Tables 4 and 5 discuss the possibility of end consumers experiencing discomfort following an efficiency advise/recommendation suggestion to consumers. For instance, a recommendation to replace 25% of lighting sources (with a CFL or LED) may result in an achieved 50% saving on energy bills. Similarly, advice that encourages consumers to turn down the air conditioners by a degree above 72 °F for a period of time to attract up to a 1 to 3% bill reduction can also be associated with some level of discomfort, especially during the cooling season. As such, by advising consumers to keep the temperature as low as possible at night by turning heating or air conditioning off at night, coupled with an insulation upgrade, to save up to 30% on energy bills. For example, by advising consumers to reduce AC (12,000BTU) usage from normal 7-hour operation by a smaller and more efficient AC (10,000BTU), consumers can save 2050 W (2.05 kW) reducing peak energy consumption demand and improving efficiency EER from 3.69 to 8.33 but with a possible discomfort of 2000BTU per hour with an accumulated 42.6% level of discomfort in just 24 h, as can be seen in Table 5. Also, by advising consumers to reduce their shower time (power shower, 7.5 kWh) to 5 min from the average 45-minute behavior of consumers, there is a possible introduction of discomfort. A similar case is with the recommendation tip suggesting that consumers hang-dry clothes rather than use the drying cabinet (2.32 kWh). These recommendations have huge potential to save consumers some money but also increase the level of human discomfort (details in Table 5).

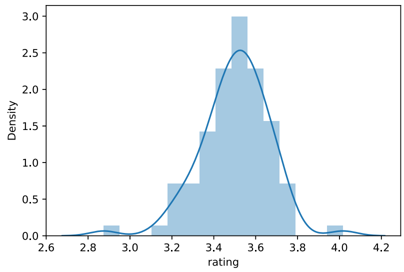
Table 3
Ranking scores for multidimensional flexible load profiles towards downward ramping.

	Components	Ranking		
		Score 1	Score 2	Score 3
Load 1	Original profile	0.292	0.416	0.292
Load 2	PV panels	0.388	0.388	0.223
Load 3	PV + BESS	0.292	0.416	0.721
Load 4	PV + BESS + MARLISA	0.326	0.486	0.188

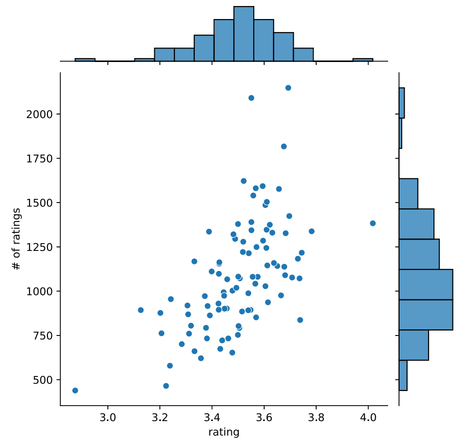
Fig. 6(a) and (b) respectively show the rating distribution and the plot of the joint behavior of rating and number of scores for electricity consumption profiles for scoring each consumer load and battery profiles plotted as density or frequency associated with each score. The left-hand side plot depicts the frequency distribution of the consumption profile scores within a given interval, and the right-hand side plot shows the visualization of the probability distribution of number of load advice alongside ratings based on their frequency of occurrence using a scatter plot and marginal histogram. The highest rating density was associated with ratings 3.5 which targets recommendations for BESS in our case.

Table 9 is an illustrative example of recommended tips for optimizing battery performance and flexible loads. This table comprises predicted scores for various potential services the framework comprises. The table also depicts a list of recommendation tips for optimizing battery performance and DR. This targets consumers for personalized recommendations and efficiency tips for improving battery performance and demand side electricity behaviors. The parameter BAT_R was associated with the highest scores since the comfort constraint keenly depends on battery availability and its availability greatly influences end users' desire to achieve their energy efficiency goals. Some samples of recommendation tips/advertisements (ads) targeted at optimizing battery performance are given as follow (Dunlop & Farhi, 2001):

1. Recommendation ads 1: A recommendation for increasing battery size can result in greater autonomy, increased time for recovery from low battery state of charge, lower battery charge and discharge rates, and cost savings.
2. Recommendation ads 2: Insufficient charging due to stratification occurs when the state-of-charge is kept low. The major problem is that the PV array (solar resources) is too small and could not generate enough electricity to fully charge the battery to its full capacity. Battery users can attain higher capacity at low state-of-charge by maintaining a specific gravity of 1.30 or higher in cold climates.



(a) Rating distribution for electricity consumption profile



(b) Rating vs. number of ratings distribution for electricity consumption profile using scatter plot with marginal histogram.

Fig. 6. Description of ratings and rated energy saving advice distribution for electricity consumption profile.

Table 4
Load hour reduction with demand side recommendation scheme.

	Load rating (kWh)	Max load duration	
		Prior advice (h)	Post advice (h)
Heat pump	4.7	16 (1, …,11;20, …,24)	8 (8, …,11;20, …,24)
Central AC (4000BTU)	6.7	7 (12, …,18)	4 (12;14;16;18)
Drying cabinet	2.32	3 (1;21;23)	1 (1)
Power shower	7.5	1.5 (8;19)	0.083 (8)

Table 5
Consumer comfort index with demand side recommendation and multi-agent RL control scheme.

	Comfort level		
	Prior advice (%)	Post advice (%)	Increased % with RL + advice (%)
Heat pump	100	50	50
Central AC (4000BTU)	100	57.4	42.6
Drying cabinet	100	33	67
Power shower	100	5.53	94.47

Table 6
RL achieved scores for MARLISA and SAC baseline towards demand reduction.

	1-load factor	Net energy demand	Peak demand	CO2 emission
SAC	1.0967	1.008	1.0869	1.015
MARLISA	1.1268	0.9991	1.2045	1.007

Table 7
Benefit and avoided operational cost analysis for 120 h simulation period.

	Peak load (kW)	Peak reduction with DSM (kW)	Reduction (%)
PV no BESS	374.56079	111.9476	23.0104
SAC	373.4	113.10839	23.249
MARLISA	367.3	119.20839	24.5028

Table 8
Benefit and avoided operational cost analysis ($) for 120 h simulation period.

	Cost with DSM ($)	Cost reduction with DSM ($)	Reduction (%)
PV no BESS	89.8946	26.8674	23.0104
SAC	89.616	27.14601	23.249
MARLISA	88.152	28.6100	24.5028

3. Recommendation ads 3: To maintain a high battery state-of-charge by limiting excessive load in periods that fall below the average insolation for manually controllable loads. Maintaining a high and consistent specific gravity in lead acid batteries and avoiding undercharging or the need for battery equalization helps to maintain high battery health (Dunlop & Farhi, 2001).

With the effect of the recommendation, provided electricity consumers are able to implement the knowledge acquired towards DR actions. However, in other cases where consumers could not perform the expected actions suggested by the recommender scheme, the framework allows end users to default to the RL control scheme. In this study, the experiment compares the performance of a baseline control scheme using SAC with the MARLISA scheme.

5.2. Control

Table 7 reports the effect of the control schemes when compared to BUA/baseline without DSM scenarios for a 120-hour simulation period. It shows that MARLISA was able to achieve a 24.5% reduction from 486.5 kW to 367.3 kW in peak electricity demand, when compared to profiles recorded without DSM indicating a peak reduction

Table 9
Energy service recommendation result.

Category	Recommendation tips	Predicted score
BAT_R	Install renewable energy storage on site to reduce climate change levy payments	1.0000
REC	Install insulation in cavity/solid walls to reduce (up to 1/3) heat loss through wall	0.558823
EFF_R	Replace 5 of home frequently used lighting with ENERGY STAR energy-efficient bulbs to save 75	0.477103
BAT_R	Install battery storage to achieve up to 42% reduction in electricity demand	0.471289
REC	Install hot water thermostat to control water temperature from tap	0.453100
BAT_R	Operate/Charge battery at optimal temperature 25 °C to protect battery and reduce demand	0.42588
EFF_R	Turn down radiator thermostat temperature by one notch	0.428970
EFF_R	Turn off appliances when not in use to save between 50 to 90 euro	0.422485
EFF_R	Wash clothes at 30 °C daily to save up to 10 euro annually	0.420108

of 199.208 kW. Furthermore, in terms of control scheme, MARLISA achieved an additional 6.108 kW savings when compared to SAC performance.

Table 6 above describes the individual RL scores as an outcome of the MARLISA model performance compared to SAC (baseline). The proposed model produced a significant reduction in net energy demand of 1.008 unit reduction when compared to the SAC baseline controller 0.9991 unit. Similarly, a significant improvement in load factor was recorded in the case of MARLISA with about 2.7446% increase compared to the SAC. MARLISA shows outstanding potential for reduction in net energy demand with about a 0.882937% decrease, which is a main objective of the study.

Furthermore, Figs. 7 and 8 describe the outcome of reinforcement learning based controllers when applied to the control of end user load profiles along with the application of hybrid BESS-solar PV towards downward ramping of consumer demand over a period of one year for microgrid end users running baseline controller and efficient MARLISA controller.

Fig. 7 describes the effect of the baseline SAC control scheme on the end consumer load profile. The result shows that the baseline scheme achieves a significant amount of load clipping of about 24.687% peak load reduction compared to the simple application of solar PV as a DR solution. Similarly, Fig. 8 depicts the load control action of MARLISA. As the figure shows, MARLISA performs significantly better than the scenario, utilizing only PV recording about a 24.5028% overall reduction in net electricity consumption.

Fig. 9 visualizes the performance of the proposed control scheme against the baseline using a violin plot. As shown by the width of case 3 (see Fig. 9), result provides a compelling proof of the high propensity of MARLISA in reducing or clipping peak load (starting from 400 kW) when compared to both cases 1 and 2 with relatively thicker regions or width size while reducing net electricity consumption as shown in the height. Compared to Fig. 10a, the baseline SAC also shows significant potential for clipping peak load, a result which generally falls short when compared to MARLISA performances.

Fig. 10 illustrates the chart of temperature compensated voltage battery charging. As was seen in Fig. 10, temperature variation pattern provides a realistic approach for charging the electric BESS in order to meet optimal operation criteria. In comparison to static charging voltage (using constant 14.4 V), this approach guarantees not only extended battery shelf life year but also a significant amount of savings of about 519 kWh recorded in annual savings in 9000 simulation hours of 375 days using a 7 Ah system charger configuration when compared to static charging voltage or approach, especially when active cooling technology is not installed or deemed too expensive.

Finally, the analysis of benefits and avoidance operational costs was shown in Table 8, which describes the cost reduction in USD ($) using the proposed RL control scheme with an original electricity unit cost (flat tariffs) of 0.24 $ per kWh or 0.22 € per kWh for household consumers obtained from Eurostat (European Union, 2021) for first half of year 2021. Original cost without DSM relating to 486.50839 kW consumption was 116.76201 $ per kWh compared to DSM control scheme, MARLISA was able to achieve about 24.5% cost reduction from 116.76201 to 88.152 $. Similarly, MARLISA outperformed SAC which recorded about 1.259% higher cost.

6. Evaluation

In order to evaluate the quality of the decision of the recommender system, metrics such as RMSE, and consumer comfort index (CCI) were considered. The recommender systems was evaluated using a strategy for proving the effectiveness (decision quality) and efficiency (decision efforts) of recommendations provided to systems operators, consumers, or human agents based on the user's perspective. The recommendation evaluation strategy shows how to improve the quality of decision while decreasing the required discomfort for such a decision, especially when compared to the scenarios achieved when there is no exposure to decision support models. In this case, CCI has been adopted to cross-examine the effect of energy efficiency advice on end consumers.

Again, based on the evidence from Figs. 7, 8, and 9, it is clear that the proposed MARLISA agent can be associated with a lot of benefits towards the reduction of net electricity consumption while significantly improving the comfort constraint experienced by end users. Another important finding of this study is that the application of the control scheme did not only improve the comfort level of consumers but was also able to achieve up to 24.5% reduction in the net cost of electricity in the case of MARLISA.

A final remark on the current work refers to the comfort constraint that this study attempts to bring into DSM. The potential for comfort improvements significantly holds the promises for easy adoption of conservation schemes at the user end. As such, the study attempts to improve adoption of such and similar schemes based on the proposed framework.

6.1. Challenges and practical implications of the proposed model

Challenges of the proposed model: We observed some challenges relating to bad data resulting from poor cyber security and/or communication failures. The reported bad data has the potential to be hidden in the huge amount of historical data collected and could result in aggregators' or end-user's' inability to make correct control decision (Tao, 2016). Similarly, another potential challenge to the proposed model is the rate of adoption, which is often associated with new or emerging technologies (Mohd et al., 2008).

One limitation of the proposed framework includes the need for historic/logged data from past scenarios so that they can be useful for purposes such as training of the RL model, without which it can be difficult to execute the proposed framework. In order to mitigate such limitations, data obtained from identical buildings can be useful in kick-starting the framework. From the regulatory or economic perspectives, there are no limitations currently preventing the application of the proposed framework. Although the current approach adopted for regulation of flexible trading and DR is not open enough for a sufficiently widespread application of the proposed model (Pinto et al., 2019).

Practical implications: The presented case studies revealed that the proposed framework was suitable for the provision of appropriate recommendations targeting the amount of electricity reduction for the microgrid energy management context. Importantly, the proposed model requires the installation of a communication channel within

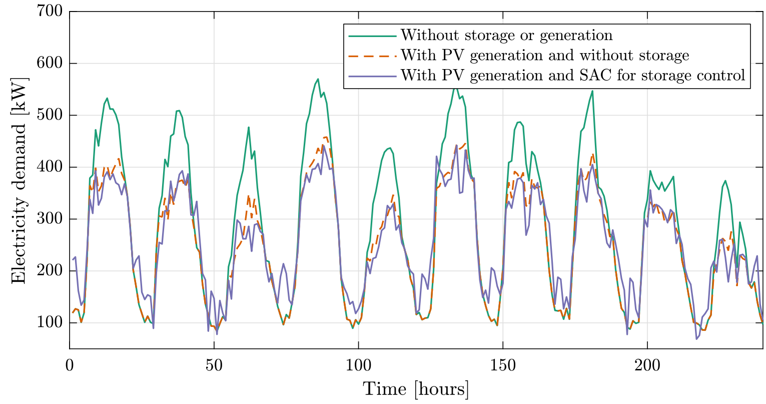


Fig. 7. Plot of electricity demand without storage (kW), electricity demand with PV generation and without storage (kW); electricity demand with PV generation and Soft-actor critic (SAC) scheme for storage control (kW).

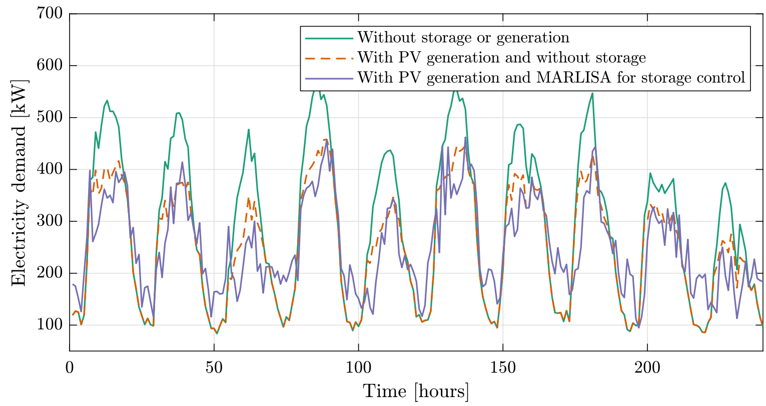


Fig. 8. Plot of electricity demand without storage (kW), electricity demand with PV generation and without storage (kW); electricity demand with PV generation and MARLISA for storage control (kW).

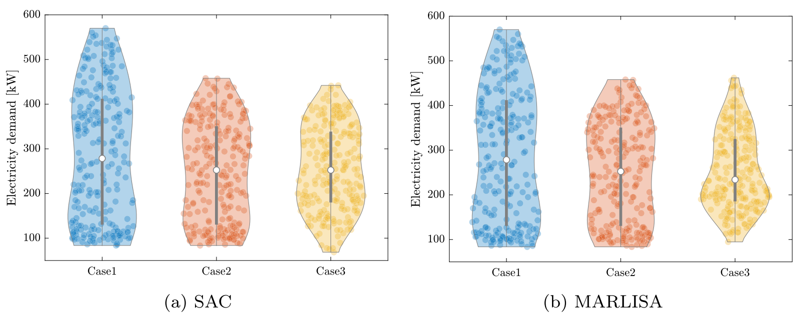


Fig. 9. Plot of net electricity demand recorded for various scenarios; Case 1: without storage; Case 2: with PV generation and without storage; Case 3: with PV generation and SAC (left plot) or MARLISA (right plot) for storage control.

the microgrid between consumers and other microgrid entities when deployed in the field. The requirements for deployment of the proposed model are easy from the aggregators' perspective simply by providing them with a log of the analysis from previous cases alongside access to information characterizing new scenarios. From the consumer's perspective, there are limited implementation barriers for the framework aside from the installation of communication channels for the flow of information. The implementation of the methodology allows for the provision of recommendations that can be sent to buildings or installations within the microgrid, as such the result is not dependent on the approach each consumer applies the recommendations. Generally, various application scenarios such as BEMS or manual application approach can be considered. Irrespective, the recommendation provision does not directly rely on the actual control scheme (MARLISA in our

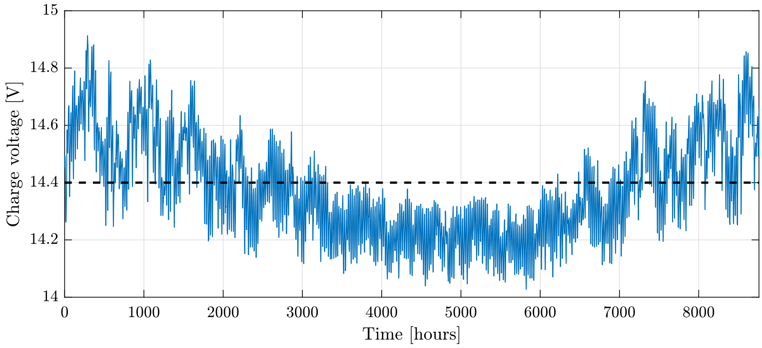


Fig. 10. Temperature compensated voltage battery charging.

case), but vice versa. Again, the proposed MARLISA based demand side recommender scheme significantly reduced end-users' discomfort, making it easier to convince end-users to adopt the proposed model and promoting an impression that the models will likely gain easy adoption from the end-user.

A long-term BESS deployment approach can have a significant impact on the microgrid optimal operation. In addition to achieving the goal of balancing the equation for demand and supply, especially during the periods of excess or shortage, they are useful in serving the purposes of dispatchable DG units capable of operating at maximum efficiency, thereby curtailing the need for the deployment of expensive sources of energy during the peak hours. A real-life demonstration in the study presented shows that optimal control of the long-term BESS scheme produces up to a 64% reduction in the cost of most demand Olivares et al. (2014).

From the perspective of decarbonization, the study has some policy implications relating to carbon reduction goals. In this study, policy implications were also addressed with the amount of carbon reduction archived (about 0.79%) by the proposed model (see Table 6) thus boosting the potential for achieving the carbon reduction targets and making the framework a viable candidate for carbon-cutting initiatives. Policymakers and decision-makers alike can also view the framework as a means for increasing the amount of revenue accrued from emission allowance auctions. Hence, the proposed framework can be considered as a useful tool in support of agendas targeting the formulation of carbon reduction policies, legal and regulatory frameworks.

7. Conclusion

An energy efficient behavior model based on an e-commerce demand side recommender system (i.e., rating prediction and top-N recommendation) and a multi-agent reinforcement learning control model for smart grid applications has been proposed. Additionally, a new set of integrated energy services recommendations based on three menus/category elements (i.e. `BAT_R` and `EFF_R`, `REC`) was proposed. Similarly, the proposed system suggests value-added services that are required to support the continuous and sustainable operation of the BESS. As such, we implemented a design of a vertical prototype that incorporated the recommendation of the battery-based value-added services alongside a classic demand side recommender system. Furthermore, microgrid consumers using battery-based DR require battery-friendly usage advice. Therefore, for a hybrid PV-BESS, this study proposes the use of a demand side recommender system that informs consumers of the usage condition and advises on conditions the battery might experience in current and future situations. Based on literature, essential functionalities of decision support system, in view of a generic requirement for a demand side recommender system for a hybrid PV-BESS were satisfied. Further discussion on their use case scenarios, alongside implementation of the initial design decision of recommender system was presented. The study utilized a content filtering recommendation model for the provision of recommendations for the integrated energy services. Finally, a demonstration of the proposed model's effectiveness was conducted using a simple case scenario of 9 households on a microgrid network. The result shows that the proposed framework was able to achieve up to a 24.5% reduction in overall energy consumption. The model was tested with a variety of demand profiles and climatic conditions to show the effects of various demand profiles on the results. In addition, the framework was used to model full-year operations, which suitably accounted for full-year seasonal differences and dynamic prices. Furthermore, experimental results show that proposed multi-agent reinforcement learning model successfully helps consumers achieve improvements in overall system operation while reducing end-users' discomfort. Another benefit of the developed MARLISA based control scheme is that it is model-free and easily adapts to the increasing availability of data to help consumers develop capacity for a cost-effective demand response. Furthermore, the proposed framework deploys a simulation framework that is suitable for pretesting the control scheme for various possible consumption scenarios, resulting in a robust and reliable system.

We observe some potential challenges that need to be overcome towards the full practicality of the proposed multi-agent RL-based framework. Some of them include efficiency and reliability resulting from limitations in data availability and the dynamic nature of the environment. Similarly, in spite of the great benefits associated with BESS in DSM applications, their cost may be a limiting factor for their real-life applicability.

In the future, the proposed model can be extended to cater to possible grid attack scenarios, other security bridges, and also extended study on the integration and management of V2H (vehicle-to-home) or electric vehicle considerations, which has the potential to play a crucial role in the future grid. Again, future efforts will be committed to improving upon the existing feature extraction methods as sentiments correspond to features and the intensity of the sentiments associated also needs to be studied. Based on this, we propose to improve upon the existing recommender system algorithms by adding the dimension of context to the recommendation algorithms.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The work was partly supported by the Estonian Research Council grants PRG658 and PRG1463. The work of A. E. Onile in the project "ICT programme" was supported by the European Union through European Social Fund. Y. Levron was partly supported by Israel Science Foundation grant No. 1227/18.

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Appendix 6

VI

A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Applications of digital twins for demand side recommendation scheme with consumer comfort constraint. In *Proceedings of IEEE PES ISGT Europe 2023 (ISGT Europe 2023) – 13th International conference of IEEE PES ISGT Europe Conference*, 2023

Applications of Digital Twins for Demand Side Recommendation Scheme with Consumer Comfort Constraints

Abiodun E. Onile, Juri Belikov
Department of Software Science,
Tallinn University of Technology,
Akadeemia tee 15a, 12618 Tallinn
{abiodun.onile,juri.belikov}@taltech.ee

Eduard Petlenkov
Department of Computer Systems,
Tallinn University of Technology,
Akadeemia tee 15a, 12618 Tallinn
eduard.petlenkov@taltech.ee

Yoash Levron
Faculty of Electrical & Computer Engineering,
Technion—Israel Institute of Technology,
Haifa, 3200003, Israel
yoashl@ee.technion.ac.il

***Abstract*—The next evolution of traditional energy systems towards smart grid will require end-consumers to actively participate and make informed decisions regarding their energy usage. Industry 4.0 facilitates such progress by allowing more advanced analytics and creating means for end-consumers and distributed grid assets to be modelled as their Digital twins (DT) equivalents, paving the way for asset-level analytics. Noteworthily, consumers' comfort is crucial towards promotion of easy adoption of such models from consumers' perspectives. This study presents the application of hybrid DT and multiagent reinforcement learning models for real-time estimation of end-consumers future energy behaviors while generating actionable recommendation feedback for improving their energy efficiency and enhancing end-user comfort.**

***Index Terms*—Industry 5.0, Hybrid digital twins, Demand side recommender system, Distributed power systems, Consumer comfort**

I. Introduction

The worldwide electricity grid is facing an unprecedented rise in demand and needs reliable supply of electricity at the same time. There is a need to restructure the prevailing energy system to curtail this breach in demand and supply [1], [2].

The traditional electricity grid is unable to meet up with/fulfill requirements for the growing demand, nor effectively address needed Demand Response (DR) programs [3]. Again, traditional DR requires consumers and energy managers to analyze several set-points and their implications in order to effect DR on the electricity grid. This is a task that can be considered extremely difficult to accurately accomplish by a human operator and consumers alike [4]. This situation thus calls for the deployment of novel approaches.

Distributed energy resources (DER) coupled with Battery energy storage systems (BESS) provide a suitable solution. Similar problems relating to information filtering and the effective participation of microgrid assets at the asset-wise (rather than system-wise) level/layer such as behind-the-meter resources (BTM) for improved analytics however, exist. This is due to challenges related to the increasing deployment of BESS to meet DR needs. This problem is not trivial since individual BESS often possess several operating configurations that might be difficult to understand by consumers [5].

Industry 4.0 digital twins provide opportunities for a deeper level of analytics and intelligence extraction from data. Recent studies revealed that effective end-consumers of Industry 4.0 will be required to merge their knowledge with the DT replica of microgrid assets (or the reconfiguration of BTM assets) with necessary programmed analytics skills [6]. In light of Industry 4.0 advances, upcoming Industry 5.0 [7] holds immense promises to revolutionize end-consumer behavior in aspects relating to servitization such as personalized information and e-commerce [8] recommendation services. These Industry 5.0-enabled personalization and customization are based on the capabilities that all DT replicas of microgrid assets are trackable, which thus allows for the implementation of an end-user feedback loop [9] using a recommendation scheme.

Demand side recommendation systems [10] are used to provide end-consumers with actionable recommendations of various energy-efficient products and services by learning the interests and preferences of end-consumers obtained via predicted and historic energy data. Noteworthy, even with available energy efficiency information, consumers are reluctant to carry out suggested actions, such as shifting their energy usage schedule [11]. Following this, some studies advocate the introduction of a direct consumer feedback scheme for discomfort using an objective function, which gives way for manual override of recommendation to allow users' preferences [12]. This situation calls for a comfortable solution.

From the literature perspective, work [13] presented a study on human-centered lighting comfort at the workplace using Industry 4.0. The author in [14] presented a work on a building thermal comfort management scheme based on the integration of building information management (BIM) and internet of things (IoT). In another article, authors [15] presented an In-

The work was partly supported by Estonian Research Council grants PRG658 and PRG1463, and by Israel Science Foundation grant No. 1227/18. The work of A. E. Onile in the project "ICT programme" was supported by the European Union through European Social Fund.

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dustry 4.0 based demand side energy management assessment scheme for enabling comfort-oriented product service systems (PSSs) in buildings Energy Management System (EMS). Work [16] describes the application of Industry 4.0 for managing the lifecycle of smart heating systems. Study outcomes revealed significant improvements in users' comfort levels alongside an increased reduction in energy consumption.

Although these solutions have considered consumer comfort, they are less adaptive/scalable when considered from the microgrid perspective and do not make an effort to present the benefits of advanced predictive analytics associated with the proposed hybrid DT model of individual microgrid assets. Against this backdrop, the current study focuses on the further development of demand side recommender schemes based on a novel ensemble of technologies, such as hybrid DT and multiagent reinforcement learning (RL) models, that enable an increase in end-user comfort on a distributed power grid.

The novelty of this study is highlighted in the introduction of an ensemble of hybrid DT and a separate/independent class of active energy storage systems controller for regulating BESS technologies by separating them from loads that determine consumer comfort alongside facilitation of energy efficiency optimization around individual microgrid assets or devices, thereby allowing simulation at specific microgrid component levels rather than solely optimizing for end-users general energy behaviour while helping end-users achieve their energy efficiency and comfort goals.

II. METHODOLOGY

A. Hybrid Digital Twins

The Digital twin modeling was approached using a combination of a physics model based on a first-order ordinary differential equation (ODE) solver and a recurrent neural network (RNN) based on

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-d_y)) \tag{1}$$

for generating end-user electricity behavior prediction and implementing demand side management measures on the microgrid. In (1), y denotes the historic energy demand over time (t), where d_y is RNN output lagged feedback.

The physics model was designed based on the physical layout of microgrid assets and components and the configuration/specifications of the reference system. The proposed model of a distributed grid system comprises a 66 kV network of distributed system consisting of the following major components: Heating, Ventilation, and Air Conditioning (HVAC), Air filtering system and BESS (Li-ion battery).

Physics based model describes the load classes of microgrid assets and the numeric solutions governed by the equation describing their energy behavior.

Battery physics model. The model equivalent of BESS was developed to obtain a comparison between the resulting physics model and the real asset. The modeling of the BESS was used to effectively address challenges associated with the performance and lifetime prediction of the BESS, as a poorly performing battery can have an adverse effect on end-user conservation goals [17]. The physics model of battery capacity evolution over cells' lifetime is described in the following equation as [18]

$$C = C_0 e^{k\frac{iT_c}{t_i}}. \tag{2}$$

Additionally, the expression for battery degradation in relation to capacity is expressed as

$$L = 1 - \left(1 - L^{'}\right) e^{k\frac{iT_c}{t_i}}, \tag{3}$$

where T_c represents the cell temperature, L is the lifetime of the battery, $L^{'}$ is the initial lifetime, t_i represents the charge time per cycle, C_0 denotes initial capacity and k is assigned a value of 0.13.

HVAC Air filter clogging physics model. It is important to have a reliable model of HVAC air filter pressure as an increase in pressure drop can result in increased energy consumption and a significant drop in efficiency below cooling satisfaction levels that are considered to be desirable. Although, occasionally, maintenance of HVAC systems may be overlooked, this often results in severe consequences for the HVAC system and its energy consumption profile. A model description of the air filter based on a filter clogging investigation pertaining to fan power consumption, air quality, and filter efficiency subject to the measured outdoor air concentration is described in the following equations [19]:

$$m = Q_v \nabla t (C_e - C_s)\,[\mu g] \tag{4}$$

and

$$V \times \frac{\mathrm{d}C}{\mathrm{d}t} = C_s Q_v - C_r Q_v, \tag{5}$$

where m denotes the mass accumulated in the filter at each time step t, C_s is the supply air concentration, C_e represents the outdoor air concentration, C_r is the homogeneous room air concentration, V is the room volume, and Q_v is the outside air flow rate.

B. Recommender Systems

Consumer behavior profile rating. The problem of describing consumer behavior was approached based on the application of graph-based analysis. It is possible to model consumers' energy transition frequency [20]. A time-varying flow performs a significant role in the evolution of behavior graph topology (i.e., the rise and fall of nodes and edges) towards the description of a microgrid end-consumer electricity profile (i.e., base (b), mid (m), and peak (p) load). Again, link prediction constitutes an important study problem in the domain of network evolution because it helps determine the links that will evolve in the future. Ranking consumer energy consumption was carried out using analysis and prediction of load dwell time, which was useful in alerting end-users of deviations in behavior or frequently occurring load profiles. A rating matrix was established using the results from the predicted or forecast profile, and is defined as

$$G_{M\times N} = \begin{bmatrix} b_{11} & m_{12} & p_{1n} \\ b_{21} & m_{22} & p_{2n} \\ b_{m1} & m_{m2} & p_{mn} \end{bmatrix}. \tag{6}$$

Here, every row (M) of the rating matrix describes a microgrid asset (i.e., user, BESS, etc.), while the microgrid assets' load profiles are represented by the column (N).

In this study, the behavior model was defined as a ranking problem, which can be depicted as follows: Given that $G = (V, E)$, a set of nodes is represented as V and a set of edges or links is represented as E. An appreciable behavior attempts to identify points with the lowest consumption while at the same time associating them with the highest scores. A graph-based ranking model was given consideration due to its tendency to compute scores with superior performance, as reported in [20]. The recommendation scheme was configured to select flexible loads associated with higher scores obtained from forecast data, and in this case the PageRanking algorithm (see equation 7) has been considered for obtaining scores from raw data [20]. PageRank can be defined as

$$\mathrm{PR}(V_i) = (1-d) + d \sum_{i=1}^{N} \frac{\mathrm{PR}(v_i)}{N(V_i)}, \tag{7}$$

where d represents the damping factor, N depicts the total number of assets' load profiles pointing to profile V_i, and $\mathrm{PR}(v_i)$ represents the currently ranked load profile. The recommender systems suggests top-N efficiency tips to consumers based on currently ranked load profile. In situation where consumers find significant discomfort in effecting suggested efficiency recommendations, the framework defaults to multi-agent RL control scheme for BESS technologies for peak load reduction and comfort improvements.

C. Multi-agent Reinforcement Learning with Iterative Sequencing Action (MARLISA)

This aspect of the methodology describes the use of a multi-agent reinforcement learning model in the control of the BESS technologies. MARLISA helps to facilitate the coordination among agents based on reward sharing in a decentralized, anonymous, and scalable way. Each agent is expected to participate by sharing two variables, which makes the algorithm scalable and ensures stability [10], [21]. This is subject to the condition that the number of variables that each agent requires does not increase with the agents' number. In essence, the MARLISA model is useful for decentralization-related multi-agent problems that can come up in load coordination problems. The RL agents generate a number of control actions while receiving a set of states and rewards in return. At any moment, the RL model makes a decision on the quantity of energy to store or release/supply for cooling or heating. Buildings energy demand satisfaction is guaranteed at all times by the microgrid RL agents before storing additional/excess energy. RL control is formulated as a Markov decision process (MDP) in equation (8). MARLISA model is presented in Fig. 1), implemented by equipping each house on the microgrid with an individual RL agent. From the power system perspective, the agent is required to learn how to shape the overall load profile of the microgrid. Specifically, each agent was evaluated based on their ability to achieve reductions in net peak demand, daily average peak, total ramping, net annual demand, and user dissatisfaction minimization on the microgrid. Parameters of the multi-agent model used include a neural network architecture with a 256×256 size of the hidden layer, a learning rate of $lr = 3 \times 10^{-4}$, batch size = 256, decay rate $t = 5 \times 10^{-3}$, and ydiscount=0.99.

$$V^{\Pi}(S) = \sum \Pi(S, a) \sum \mathrm{P}^{a}_{ss'} \left[\mathrm{R}^{a}_{ss'} + \gamma V^{\Pi}\left(S'\right) \right]. \tag{8}$$

Here, MDP comprises of a set of state S and action a. Where $R^{a}_{ss'}$ represents the reward and $P^{a}_{ss'}$ is the transition probabilities for moving from initial to a new state s'. $V^{\Pi}(S')$ is the agent's expected return and discount factor for obtaining future rewards is given as $\gamma \in (0, 1)$. Again, Π represents the policy function.

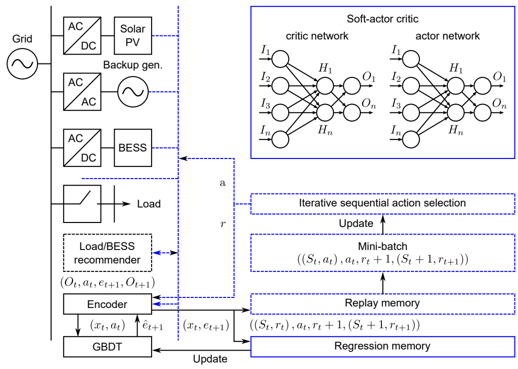

Fig. 1. Simulation framework for MARLISA model in end-consumer energy-BESS recommender scheme based on microgrid network's key components.

D. Evaluation Metrics

The study adopted the following evaluation metrics: Root Mean Squared Error (RMSE), Mean squared error (MSE), Mean absolute error (MAE), Mean absolute percentage error (MAPE), Cost Benefit Analysis (see Table I) and Consumer Comfort Index (CCI). The CCI metric is defined as the ratio of the number of hours which a device is out of service due to recommended advice to total number of hours a device is in service [10].

TABLE I
MATHEMATICAL EQUATION OF VALUATION METRICS

Metrics	Equation
Root mean squared error (RMSE)	$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2}$
Mean squared error (MSE)	$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2$
Mean absolute error (MAE)	$\mathrm{MAE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert p_i - q_i\rvert}$
R-squared (R^2)	$R^2 = 1 - \frac{\sum(p_i - q_i)^2}{\sum(p_i - \bar{q}_i)^2}$
Mean absolute percentage error (MAPE)	$\mathrm{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\lvert\frac{p_i - q_i}{p_i}\rvert$

Consumer Comfort Index can be defined as

$$CCI = \frac{\text{\# of non-recommended hours of operation}}{\text{Total \# of hours of period of operation}} \times 100. \quad (9)$$

III. Numerical Results and Analysis

This section discusses the results of the experiments. The resulting hybrid DT models of Li-ion battery, and HVAC air filter were useful in predicting the future behavior of the specified microgrid assets. Annual outdoor hourly measured PM2.5 concentration dataset for modelling airfilter was obtained from Airparif [19]. Again, NASA dataset was used for modelling the Li-ion battery [22].

TABLE II
Comparison of Valuation Metrics for Physics and Hybrid DT Models Predictions for Selected Microgrid Assets

Asset	Model	MSE	R2	MAE [kW]	RMSE	MAPE [%]
Air filter	physics	44.929	0.918	4.995	6.703	0.123
	hybrid DT	7.1294	0.988	2.56	2.67	0.051
Li-ion	physics	0.122	-2.5736	0.2964	0.3493	0.2074
	hybrid DT	0.0003	0.9917	0.0145	0.0169	0.0101

TABLE III
Consumer Comfort Index with Demand Side Recommendation and Multi-agent RL Control Scheme

Items	Comfort level		
	Prior advice [%]	Post advice [%]	Increased % with RL + advice
Heat pump	100	50	50
Central AC (4000BTU)	100	57.4	42.6
Drying cabinet	100	33	67
Power shower	100	5.53	94.47

Figure 2 shows a comparison of the proposed hybrid DT with the physics model and sensor data observation of indoor air quality. Noteworthy, the air filter plays a key role in the HVAC system as it ensures equipment/residents are protected from airborne pollutants.

Figure 3 shows the comparison of the developed hybrid DT, physics models, and sensor data observations for Li-ion.

Figure 4 describes a comparison of predicted outcome of HVAC air filter PM2.5 profile using hybrid DT and physics model. Predicted outcomes of the filter hybrid DT was scored using equation (7) for recommendation provision targeting comfort loads (i.e. Heat-pump and Central AC).

Table II shows improved forecasting potential of proposed hybrid DT models using a physics-informed machine learning approach compared to the baseline physics model. A negative value of R2 indicates solely using Li-ion physics modelling technique poorly fits observation data to model. Table IV describes various recommendation tips targeted at microgrid assets (i.e., BAT_R for BESS and REC).

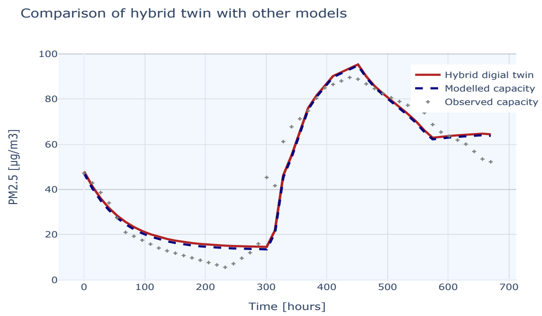

Fig. 2. Comparison of the hybrid digital twins and physics model for HVAC air quality model with a 670 hours time-range.

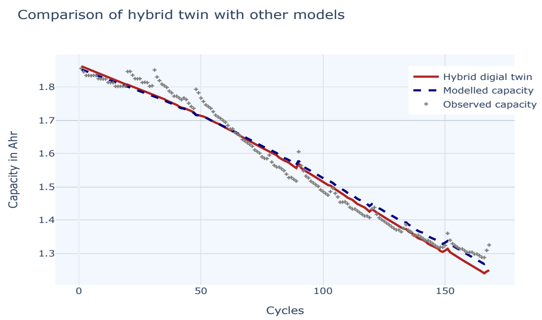

Fig. 3. Comparison of the hybrid digital twins and physics model for Li-ion discharge capacity over 160 cycle.

Figure 5 visualizes the load control action of the proposed MARLISA model on the end consumer load profile. The control scheme shows a significant improvement in comfort and efficiency performance when compared to baseline scenario (without Li-ion storage) thereby recording a net reduction in electricity consumption of about 24.5028%. To improve comfort in situations where consumers find difficulties in implementing suggested recommendations, the multi-agent RL control scheme serves as default control. Table III describes

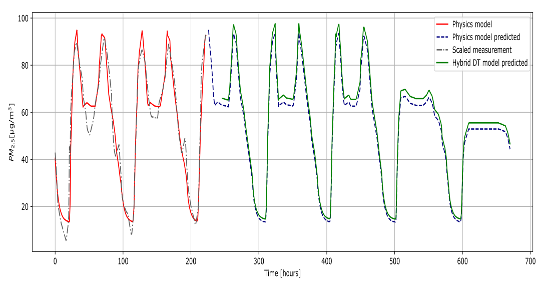

Fig. 4. Comparison of modeled hybrid digital twins and physics model prediction of PM2.5 for HVAC air filter model with a 670 hours time-range.

TABLE IV
ENERGY SERVICE RECOMMENDATION RESULTS

Category	Recommendation tips	Predicted score
BAT_R	Install battery storage to achieve up to 42% reduction in electricity demand	0.471289
REC	Change HVAC filters to save up-to 30% energy	0.453100
BAT_R	Operate/Charge battery at optimal temperature 25°C to protect the battery and reduce demand	0.42588
REC	Turn off appliances when not in use to save between 50 to 90 EUR	0.422485

improvements in comfort level following deployment of the MARLISA control scheme.

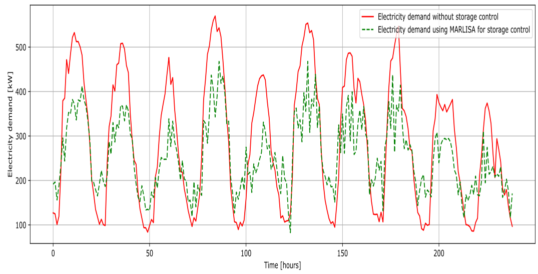

Fig. 5. Plot of electricity demand without storage (kW) and electricity demand with MARLISA for storage control (kW).

IV. CONCLUSION

From the foregoing, we have presented a study on the applications of Industry 4.0 digital twins and multi-agent reinforcement learning for demand side recommendation schemes with consumer comfort constraints in distributed power systems. Study results show about 24.5% reduction in net energy consumption alongside 94% comfort improvements in some loads. Additionally, hybrid DT achieved up to 84.132% decrease in prediction error using MSE metrics.

This study presents some limitations. First, there are limitations relating to the gathering of observation data for modeling the physics of a number of selected microgrid assets. The second is the need for the establishment of standard communication protocols between devices' DT for improved interoperability and cybersecurity-related challenges. These limitations shall be considered as a future work.

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Appendix 7

VII

A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Emerging role of Industry 5.0 digital twins in demand response electricity market and applications. In *Proceedings of IEEE PES ISGT Europe 2023 (ISGT Europe 2023) – 13th International conference of IEEE PES ISGT Europe Conference*, 2023

Emerging Role of Industry 5.0 Digital Twins in Demand Response Electricity Market and Applications

Abiodun E. Onile, Juri Belikov
Department of Software Science,
Tallinn University of Technology,
Akadeemia tee 15a, 12618 Tallinn
{abiodun.onile,juri.belikov}@taltech.ee

Eduard Petlenkov
Department of Computer Systems,
Tallinn University of Technology,
Akadeemia tee 15a, 12618 Tallinn
eduard.petlenkov@taltech.ee

Yoash Levron
Faculty of Electrical & Computer Engineering,
Technion—Israel Institute of Technology,
Haifa, 3200003, Israel
yoashl@ee.technion.ac.il

***Abstract*—Traditional power system is facing challenges demanding new operational requirements to meet targets of Net Zero Emissions by 2050. Aggregators are playing progressively important role in the demand response (DR) electricity market but are often riddled with deep level of market monopoly and lack of transparency/secrecy. Emerging real-time information technology (IT) applications and novel modelling of digital twins (DT) of individual electricity assets are challenging this position by promising improvements and openness that allows TSO direct access to available demand side flexibility. Additionally, DT technologies are facilitating how demand response services are delivered to end-users by allowing individual assets participation at the atomic level. In this study, the application potentials of assets' DT in participating in the demand response electricity market was examined. Again, an overview of DT applications for DR was conducted. The novelty of this study is highlighted in development of new approach that facilitates individual end-user assets' contribution to demand response efforts. The research identifies key useful questions that might serve as inspiration for stakeholders and policy-makers to further close existing gaps in the field of DT, smart-grid and demand response.**

***Index Terms*—Aggregators, demand response, digital twins, Industry 5.0, smart-grid**

I. Introduction

Europe interconnected power systems is undergoing transition process [1]. A number of conventional plants are already being decommissioned or are about to be put out of service while a number of volatile converters interfaces variable renewable energy (VRE) sources of energy generation and expansion of dynamic system loads threatens to impact service provision in coming decades. More importantly, there are high possibilities for reduction in system inertial and increasing amount of complex dynamic phenomena attributable to the power system [1]. Again, peak demand is ever increasing leading to increasing concerns about peak pricing where predicted additional increase in peak pricing has potential to not only strain the economy but also result into wide spread risks of power blackouts. Furthermore, dynamic deployment of distributed energy generation such as renewable energy sources (RES) has significant impact on the functions of distribution system operators (DSOs) and transmission system operator (TSO) saddled with the tasks of managing and provision of reliable system operations [2].

To deal with variability in output, introduced by renewable energy while meeting up with the demand patterns, solutions that promote flexible electricity markets which are capable of dealing with short-term errors that do not meet needed demand are required [3]. Thus, innovative services that allow VRE alignment with demand and supply alongside investments in demand response schemes for reduction in peak and overall load consumption has proven to be more constructive and proactive [4].

The aggregators are being applauded as key to enabling distributed energy resources (DERs) electricity integration and DR service provision at scale [5]. Aggregators plays crucial role in the development of sustainable grid and are often seen at the front-most part in the struggle for the adoption of DERs while serving as the crucial interface connecting the TSO/independent system operators (ISOs) and utilities with fleet of DERs towards the provision of varying services including demand response [6]. One unique challenge however is that system operators/TSOs lack direct access to the feedback information available to aggregators [6] due to aggregators' strategic ability to curtail generation resources without TSO knowledge giving them opportunities to manipulate prices. As such, the role of DERs aggregators as value creator might be temporary as the power system transition into the future [3], [5] where technological innovations and advancements in regulations are likely to takeover aggregators role and present limitations (i.e. imperfect coordination, aggregators market monopoly, etc.) are likely to disappear.

A major indicator signifying the shift from distributable large-scale centralized to decentralized, clean and personalized energy can be attributed to introduction of renewable energy (i.e., solar and wind) which facilitates the behind-the-scene

The work was partly supported by Estonian Research Council grants PRG658 and PRG1463, and by Israel Science Foundation grant No. 1227/18. The work of A. E. Onile in the project "ICT programme" was supported by the European Union through European Social Fund.

979-8-3503-9678-2/23/.00

deployment of novel digital backbones that enables the integration of grid level assets such as batteries, solar panels, wind turbines to generate and store energy at the consumer end [7].

Industry 4.0 was introduced towards the realization of the European industry transformation and production process acceleration in 2011. A decade later saw the introduction of “Industry 5.0” by the EU which emphasises sustainable development, user-oriented, flexible and adjustable technology innovation [8]. In light of the success of Industry 4.0, new approach is focusing on strategies for improving services provision and productivity compatible with upcoming Industry 5.0 and Society 5.0 [9]. Industry 5.0 can be defined as cooperation between man and machines/artificial intelligence (AI) by integrating virtual and physical space to solve production and society problems. Note-worthily, the energy system is undergoing significant digital transformation empowered by the Industry 4.0 based Internet of Things (IoT) and its antecedent the Internet of Energy (IoE) which constitutes the elements such as artificial intelligence (AI), smart meters, machine-to-machine (M2M) technology, etc. that contributes towards enhancements of the future smart energy grid [7]. With the developments around Industry 4.0 IoT, the exploration of DT unfolds gradually with focus on local equipment modelling [10]. Supported by new EU directives for legislation of creation of new services based on smart network infrastructure and interconnections [11], asset (individual electricity devices) based modelling approach to DR can hypothetically matured for integration into DR electricity market. A familiar case is the EU Energy Efficiency Directive 2018/2002 that requires that heat cost allocators (HCAs) devices must be metered and provided with remote access capabilities, allowing for development of functional DT replica [12].

Digital twins is digital representation of objects which could vary from distributed grid asset (wind turbine) to a complete city as-well as everything in-between. Recent applications have also seen DT represents intangible entities such as knowledge and services [13]. Future DT needs to transverse different system levels ranging between individual electricity asset twins in isolation while considering twins as intrinsic element of larger power systems with emerging behaviour from interactions between multiple twins [14]. By using digital replica/models, personnel can take efficient action while responding to various energy systems information and providing collaborative assistive model of all entities [15]. DT is envisioned as the next evolutionary path of power system control center as it is capable of enhancing traditional system with added functionalities such as advanced decision support and dynamic observability opening ways for various services such as analysis of system stability, planning [16] towards DR. Furthermore, DT allows system operators to analyze and engage smart assets (such as on-load tap changing transformer (OLTCT) and behind the meter (BTM) assets) in real-time for purpose of voltage regulation and grid stability [17]. Again, digital technologies are facilitating the creation of virtual power plant that uses DT to aggregate end-consumers flexibility where end-users are encouraged to modify their demand to match-up supply or switch-off their devices in-order to balance the demand and supply [7].

Supported by block-chain [2] and decision support system (DSS) [18] technologies, DT of electricity assets are potentially able to independently and autonomously participate in DR scheme. Blockchain allows secure automation of transactions within the electricity grid (automatic contracts conclusion based on fulfillment of given condition) alongside monitoring of power production and consumption by prosumers [2], [19].

The future power system will incorporate multiple entities that interacts in real-time coupled with increased adoption of active prosumers and DERs which will result into more data sharing and processing requiring DSS [20]. Continuously adaptive dynamic DT provides assistance capacity to help operators using decision support system [1]. Such DT based DSS helps balance responsible parties (BRPs) and distribution system operators (DSO) to directly and in real-time access availability/status of flexibility. Again, as demand side management transition from passive to active [1], future smart-grid electricity consumers will be required to match their knowledge with the DT of the assets to effect DR tasks. Note-worthily, power generation is shifting towards distribution networks causing bidirectional flow of power energy management system (EMS)/DR schemes need to transition from passive to active [1] where new techniques such as BTM assets participation create way for new possibilities. Encouraging asset level participation with limited or no intermediary (e.g. aggregators) can result into unprecedented synergy and interoperability level of multi assets DTs towards boosting the power systems DR operation performance, efficiency and resilience (based on DT-DT interconnection and communication) [21]. Successful implementation of one-to-one DT based on individual assets of the power system will depend on shift in design thinking [22]. As a result, this study proposes an innovative asset based modelling/design for demand response scheme targeting end-consumers and system operators. To this effect, considerations were given to hybrid DT to comprise a set of individual BTM electricity assets that may be enhanced with recommender system feedback towards provision of a set of DR services [23].

A. Summary of Contributions

This section describes the potentials of digital twins approach for electricity aggregator platforms based on digital twins of electricity assets’ real-time flexibility tracking towards participation in demand response programs and monitoring of energy grid operations. To this end, this study contributes in the following areas:

- Development of hybrid digital twins of individual end-user assets towards direct participation in the demand response electricity market inline with the EU legislation for introduction of new technology for the electricity demand response market. Proposed hybrid scheme leverage domain-specific physical constraints/laws and data-driven techniques resulting in reduced simulation-to-reality gap and enhancement in prediction accuracy.

- We provide trend analysis of emerging role of DT for DR application towards formalizing potentials of proposed framework for participation of DT in future DR electricity market.

This study proposes a novel approach for standardization of DTs modeling of electricity assets which allows secure and transparent communication among different electricity entities using hybrid DT as a decision support scheme for participation in DR electricity market.

II. Background

This section contains a brief description of the application of DT techniques for power system demand response alongside key enabling technologies.

A. Industry 5.0 Digital Twins of Energy Assets

The concept of DT was first introduced by Michael Grieves [9] with projected market size of $15 billion by the end of year 2023 and was also identified as one of top ten strategic technologies of 2018 based on predictions of future trends in research. DT can be stated as Industry 4.0 key technological pillar which creates a connection between the virtual and physical representation of an actual electricity asset [1] and facilitates prediction of electricity asset dossier/behavior, that is updated continuously using real-time dataset with interaction capacity based on permission of the actual asset [23]. Again, DT are capable of altering assets behaviour based on real-time data, analytics and visualization tools connected with the individual assets being monitored [9]. Hence DT solutions are finding wide spread applications within the energy sector [7] and can be seen as important tool towards harnessing the complexity of electricity assets towards energy service provision within the demand response domain. Figure 1 depicts the schematic representation of DT scheme road-map for demand response applications.

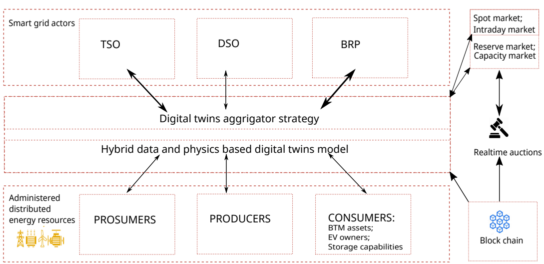

Fig. 1. Roadmap for integration of digital twins assets for demand response within the framework of Energy 5.0.

Advancements in the smartgrid technologies allow prosumers to trade excess energy obtained via renewable sources with the peer-to-peer (P2P) networks energy trading. Blockchain technology facilitate such independent DT assets' participation while playing more active role in the electricity market and allowing end-users/prosumers to maintain liquidity obtained from selling assets flexibility or micro amounts of energy [2].

B. Current state (based on Trend analysis)

This section analyses various trends of DT application in power system from literature perspective.

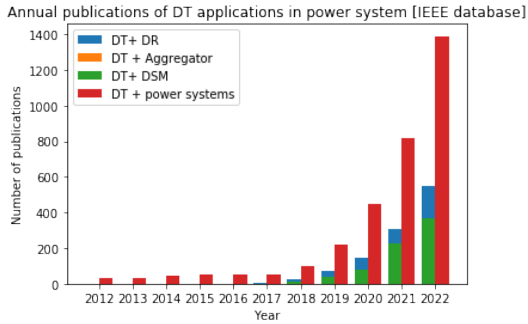

Fig. 2. Yearly publications on application of digital twins application in power system for the period between 2012 and 2022 from IEEE database.

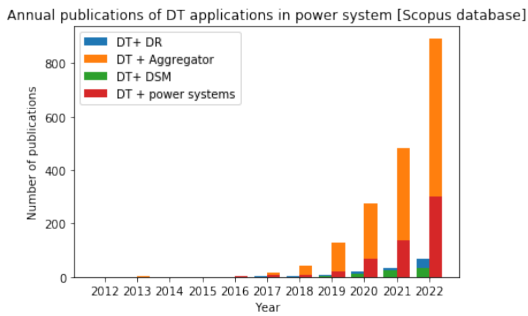

Fig. 3. Yearly publications on application of digital twins application in power system for the period between 2012 and 2022 from Scopus database.

Figures 2 and 3 describe the trend analysis of publications in the area of DT applications to power systems based on IEEEXplore and Scopus databases. To give more details about contributions and progress of the applications of DT in power systems, the result further examined key aspects such as/namely demand response, demand side management and aggregator categories. Result revealed year on year increase in publications depicting increased adoption of DT technologies in the energy sector with the highest number of 1390 publications associated with IEEEXplore in 2022. This progressive growth trend, especially as seen in 2022 reveals the likely demands for innovative consumer-centric, and sustainable demand response that DT easily leverages coupled with contribution of newly introduced Industry 5.0 and Society 5.0 concept.

C. Emerging Roles and Use-cases of DT in DR Electricity Markets

This section describes the emerging roles and use-cases of DT concept in the future energy market. The following paragraphs classifies some emerging roles of DT for power systems based on: Timescale (i.e. forecasting, model order reduction (MOR), real-time operations/state estimation etc.) and ancillary services provision for target operation/stakeholder (i.e. prognostic control, optimal decision-making, recommendation provision etc.).

- *Grid load forecasting and dynamic network reconfiguration:* Using DT technology for forecasting load can guarantee raw data reliability associatable to real-time functionality of DT [10]. Again, DT facilitates DSO center dynamic network reconfiguration by actively controlling grid assets such as contact and segment switches following load change prediction for load balancing [10].
- *Power systems real-time simulation and control (TSO & DSO):* The DT approach help with realisation of a digital close to real-time power system image consisting of the power systems state in the virtual, real space alongside state variables and stream of data connection between the virtual and physical power systems [18]. Hypothetically, DT are seen as core element of future control center with needs for communication and data-sharing between multiple DTs running several systems operator control centers and with capabilities for addressing both horizontal and vertical operations of the centers. Key benefits of such DT driven power system includes prompt discovery of abnormal grid situation, automated outages prevention recommendation provision and demand response optimization, continuous monitoring of grid and simulated behaviour (i.e. using MOR), and training of control room operator [18].
- *RES integration optimization:* Increased penetration of highly variable and intermittent RES creates challenges in maintaining system stability, DT creates detailed model of RES allowing operator to simulate impact ('what-if' scenario testing) of adding new RES on the grid.
- *Demand side recommender systems:* End-user request for service customization is further facilitated by DT of individual asset. Application of e-commerce recommendation systems [24] help in this case, by serving as feedback scheme for DT asset of end-consumers. By bringing together mixture of hyper-physical systems comprising of smart solutions and cloud computing infrastructure bases for DT, the energy sector can struck a balance between energy demand and supply, allowing proactive operation and managements, faster restoration and blackout reversals [7]. In this case both system operators and end-users can receive detailed feedbacks on the internal working of individual DT asset connected to the electricity grid alongside recommendation tips on ways to optimize the grid or consumption profiles [25].
- *Grid/Asset operation autonomy:* System autonomy can be defined as the ability of the energy system to respond to unexpected events without a need for centralised re-planning or reconfiguration scheme. An automatic system operator is trained through system life-cycle based on use of systematic learning process for updating of its experience [21]. DT provides means for such collaborative human and machine operator scheme and can help enhance human operators decision making capabilities while broadening their experience in control of grid operations especially in adverse and dynamic environments/conditions [21].

III. Methodology

This section describes the key methodology adopted by the study. First, bibliography analysis was carried out in order to examine existing literature material and determine key scientific direction associated with the research area. This is with the intention to provide thorough understanding of study problems while also identifying aspects requiring developments in the field of DT and demand response. The sequence of bibliography analysis was conducted on two major databases comprising of IEEExplore and Scopus bibliographic database. Second, a conceptual implementation describing a case study hybrid DT modelling scenario using Solar PV and Li-Ion was also presented.

A. Digital Twin Conceptual Implementation (Case study)

To verify the discussed approach, an hybrid DT platform was built to simulate the smart-grid based asset flexibility. Under this approach, a hybrid DT of Li-Ion, Solar PV and Heating, ventilation and air conditioning (HVAC) air-filter model was developed to predict/forecast the behaviour of the selected electricity grid asset.

A hybrid DT model was developed based on a combination of data driven recurrent neural network (RNN) and physics based first-order ordinary differential equation (ODE) solver (see equations 2, 3 and 4) towards forecasting/predicting end-consumers energy behavior for the implementation of demand response measures. RNN was defined as follows

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-d_y)), \tag{1}$$

where, y is historic energy demand sampled over time (t), and d_y represents the lagged output feedback.

B. Battery Physics Model

The hybrid BESS (Li-Ion) model describes the cell's resistance or capacity evolution and voltage to current response over the cell lifetime. It was developed to obtain comparison between the prediction capacity of the real asset and physics model. Specifically, the challenges associated with BESS lifetime and performance prediction can be effectively addressed/solved by modelling the Li-Ion battery towards optimizing battery performance and effecting demand response goals. The battery capacity physics model is described as

$$C = C_0 e^{k\frac{iT_c}{t_i}}. \tag{2}$$

Additionally, the expression for battery degradation in association with battery capacity is described as

$$L = 1 - \left(1 - L^{'}\right) e^{k\frac{iT_c}{t_i}}. \tag{3}$$

Here, T_c denotes the cell temperature, L represents battery lifetime, t_i is the charge time per cycle, $L^{'}$ determines the initial lifetime, k denotes assigned a value of 0.13 and C_0 is initial capacity.

C. Solar PV Physics Model

Solar PV electrical data keenly depends on solar irradiation φ, the cell or ambient temperature T and the PV systems surface area S. The output of the solar photovoltaic is modelled as [26]

$$P_{pv} = \eta S_{\varphi} \left(1 - 0.005(T_a + 25)\right), \tag{4}$$

where η denotes the PV conversion efficiency. Furthermore, φ, S, T and η determine the amount of power obtained from the solar irradiation.

D. Evaluation metrics:

Table I describes the key metrics that were used for the DT model evaluation and validation.

TABLE I
MATHEMATICAL EQUATION OF EVALUATION METRICS

Metrics	Equation
Root mean squared error (RMSE)	RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2}$
Mean squared error (MSE)	MSE $= \frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2$
Mean absolute error (MAE)	MAE $= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert p_i - q_i\rvert}$
R-squared (R^2)	$R^2 = 1 - \frac{\sum(p_i - q_i)^2}{\sum(p_i - \bar{q}_i)^2}$
Mean absolute percentage error (MAPE)	MAPE $= \frac{100}{N}\sum_{i=1}^{N}\lvert\frac{p_i - q_i}{p_i}\rvert$

IV. NUMERIC RESULTS AND DISCUSSION

Simulation Data: The actual bibliography data was collected for years ranging from 2011 to 2022 from both IEEE-Explore and Scopus bibliographic databases. Initial search returned maximum 1390 published scientific works relating applications of DT in power systems in 2022. Majority of considered publications falls into the category of demand response, demand side management, aggregators and power systems and their relationship to DT. Again, the actual operation data associated with Li-Ion and Solar PV was obtained from [27] and [28] databases from a period of 2000 and 180 simulation hours respectively.

Figures 4 and 5 respectively describe the comparison of hybrid DT prediction potentials to baseline physics model.

Table II shows the result of evaluation metrics. Results show the predominant performance of hybrid DT model of HVAC air-filter and Li-Ion battery with improved forecasting potential compared to their physics based baseline scenarios.

V. CONCLUDING REMARKS

The new era of distributed energy resources requires detailed understanding of the role of direct participation of independent assets in the DR electricity market. DT promises

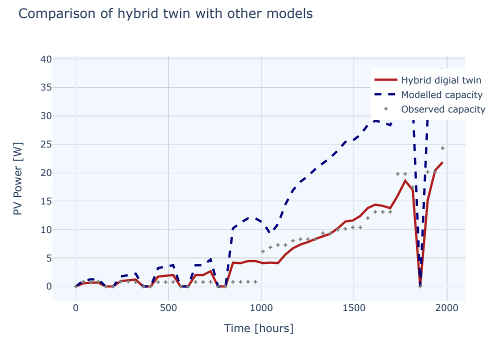

Fig. 4. A comparison between the modeled hybrid digital twins and baseline physics model prediction of solar PV model with a 2000 hours time-range.

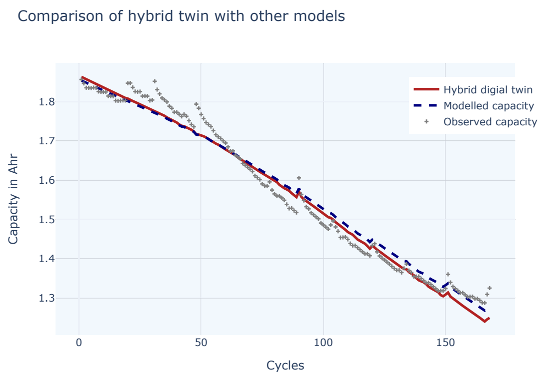

Fig. 5. A comparison between the modeled hybrid digital twins and baseline physics model prediction of Lithium-Ion model with a 180 hours time-range.

TABLE II
COMPARISON OF VALUATION METRICS FOR PHYSICS AND HYBRID DT MODELS PREDICTIONS FOR SELECTED MICROGRID ASSETS

Asset	Model	MSE	R2	MAE [kW]	RMSE	MAPE [%]
Air filter	physics	44.929	0.918	4.995	6.703	0.123
	hybrid DT	7.1294	0.988	2.56	2.67	0.051
Li-ion	physics	0.121979	-2.57355	0.296387	0.34925	0.20735
	hybrid DT	0.000284	0.99167	0.0145	0.01685	0.010128

to close communication gap by directly connecting end-consumer BTM asset and the TSO with the DT based aggregator representation of the electricity grid assets in-order to eliminate inefficiencies attributed to present DR aggregation schemes. This paper introduces a proof-of-concept for a system of multi-asset hybrid DT modelling approach that benefits from domain-specific physical constraints/laws and improved prediction accuracy for DR electricity market applications. DT key characteristics in relation to DR solution were reviewed. We view this study as the first step in the direction of the deployment and direct participation of individual distributed grid assets in the demand response electricity market via their DT replica. Current state of the art in DTs applications for DR was examined.

The study encountered some challenges which include data acquisition, data cleaning, data privacy and network security issues towards successful deployment of DT for DR schemes. Again, since the proposed scheme is at the preliminary stage, the future will determine if excessive simplified model sufficiently unveils the promises of DT scheme in DR applications.

New laws, legislation and policy implementation promoting DT in power systems targeting DR can be promulgated to further the adoption of presented architectures of DT applications. Future works will be committed to building and deploying real-time demand response feedback framework for DT assets using demand side recommender system towards achieving functional real-time flexibility aggregation and market segmentation scheme for demand response electricity market.

Furthermore, the study takes a measure to ask a set of questions towards future developments. What happens to the DT assets when the assets are retired? should experience be transferred and used in optimizing new assets? How would the electricity energy paradigm associated with demand response shift in the direction of industry 4.0 DT and what will be the role of individual grid asset DT in supporting such transition? Given a fully functional DT replica of electricity grid asset, how would they influence the performance of demand response schemes in future power systems?

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Appendix 8

VIII

A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Leveraging digital twins and demand side recommender chatbot for optimizing smart grid energy efficiency. In *Proceedings of 2023 IEEE PES Innovative Smart Grid Technologies - Asia (ISGT Asia) – 13th IEEE PES Innovative Smart Grid Technologies, Asia conference*, pages 1–5, 2023

Leveraging Digital Twins and Demand Side Recommender Chatbot for Optimizing Smart Grid Energy Efficiency

Abiodun E. Onile, Juri Belikov
Department of Software Science,
Tallinn University of Technology,
Akadeemia tee 15a, 12618 Tallinn
{abiodun.onile,juri.belikov}@taltech.ee

Eduard Petlenkov
Department of Computer Systems,
Tallinn University of Technology,
Akadeemia tee 15a, 12618 Tallinn
eduard.petlenkov@taltech.ee

Yoash Levron
Faculty of Electrical & Computer Engineering,
Technion—Israel Institute of Technology,
Haifa, 3200003, Israel
yoashl@ee.technion.ac.il

2023 IEEE PES Innovative Smart Grid Technologies - Asia (ISGT Asia) | 979-8-3503-2774-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/ISGTAsia54891.2023.10372761

***Abstract*—Electricity consumers often face the challenge of selecting an optimal plan for saving energy. Strategic energy management and monitoring plays a key role in overcoming these challenges. Developments around Industry 5.0 powered smart grid proffers adequate solutions which allows end-consumers to monitor their energy performance towards effecting demand side recommendation services. Specific problems where end-users are likely to ignore recommended advice exists, thereby contributing to widening 'knowledge-action gap'. An ensemble of hybrid digital twins (DT) asset modelling based on ordinary differential equation (ODE) physics engine and data driven recurrent neural network (RNN) prediction approach alongside PageRank based asset behavior scoring algorithm deployed for demand side recommender and generative pre-trained transformers (GPT) based conversational chatbot technology show effectiveness in engaging and extending end-consumers interests in recommended advice. The novelty of the study lies in extending current scope of demand side recommender scheme via conversational chatbot interface for DT of electricity grid assets that better engage and monitors end-user's energy behavior while offering appropriate energy efficiency advice towards achieving energy conservation goals of smart grid consumers. Extensive experiments, including evaluation of end-user studies, revealed the effectiveness of proposed approach in terms of improved recommendation quality and user engagement towards net electricity demand reduction.**

***Index Terms*—Industry 5.0, digital twins, demand side recommender, conversational chatbot, smart grid**

I. Introduction

The traditional energy industry is seen to be among the most bureaucratic and vertical industry with weak potentials for instantaneous changes [1]. The concept of Industry 5.0 with basic technologies such as Energy 5.0 [2] and Society 5.0 is challenging this ground. Society 5.0 concept is a futuristic super-smart society that allows consumers to enjoy comfortable and high-quality life based on fusion of physical and cyberspace space using ICT (information and communication technology). Industry 5.0 powered smartgrid based digital twins (DT) provides means for real-time access to the behavior and structure of the power system with aim of obtaining predictive analytics of electricity assets profile.

The work was partly supported by Estonian Research Council grants PRG658 and PRG1463, and by Israel Science Foundation grant No. 1227/18. The work of A. E. Onile in the project "ICT programme" was supported by the European Union through European Social Fund.

Digital-twins based solution (services, business modelling, multiobjective assessment and optimization) in the loop approach provides better/promising outlook compared to solely hardware or human in the loop approach [3]. Another major reason calling for deployment of advanced prediction models such as hybrid DT is due to rise in variable real-time pricing and transient renewable energy (i.e. solar power) production, power storage and sale optimization [4]. In some cases, consumers lack the technical knowledge required for wholesome evaluation of energy efficiency measures and often are seen to be disengaged from the power systems. For example units describing energy behavior such as W and kWh are abstract and has limited connotation to end user [5]. A consumer-centric approach based on Industry 5.0 that allows humans to cooperate with the energy systems cobots has recently been proposed [6]. DT technology constitutes a number of emerging digital technologies that facilitates digital transformation based on development of new business models and decision support systems (DSS) [7] towards helping consumers achieve their demand response (DR) goals [7].

Demand-side recommender system [8] promises to help user resolve conflicting information interests based on in-depth analysis of consumption behavior/profile. Electricity consumers face continuous information growth leading to daily rise in the volume of products, services or offers that are virtually impossible to directly process by users. As such, automation of electricity data processing is important [9]. Demand side recommender system intends to learn end-user specific preferences towards presenting them with relevant tips based on predicted ratings (explicit feedback)/behaviors (implicit feedback) [9]. Note-worthily, some studies revealed that in some cases, consumers manually override or ignore efficiency signals/recommendations [8] further widening the 'knowledge-action gap'.

A dialog based systems such as chatbot which utilizes conversation to filter information can bridge this gap by nudging user into imbibing energy efficient behavior using techniques that engage them in extended conversation owing to chatbots' ability to serve as companion rather than solely knowledge instructor. By design, they are capable of remembering previous conversation/interactions while offering new advice to users. This is particularly the case in the economy of instant gratification which gives consumers an impression that all their demands for information can be immediately met/granted [1] in super-intellectual Society 5.0. This is a gap that can be filled by chatbots. In this context, virtual assistant termed chatbots are used to facilitate automated and high level personalized DR customer services provision [10]. The primary use of natural language processing (NLP) for chatbots is concerned with identifying users intents associated with entities [11] such as recommended energy asset efficiency tips. Again, chatbots dynamically facilitates DT model input manipulation by stakeholders (who are majorly non-technical users) while interactively receiving response about the outcome either via structured plots or free-form text [12].

From the literature perspective, few works have examined the application of chatbot interface for the energy systems. Work [12] presented an interface using natural language for power systems. Work [11] describes an energy utility company chatbot based strategy for automating discovery of users intent in real-time. At present, there are limited schemes that interactively engage end-consumers with real-time knowledge of their peak/energy consumption details [13]. Note-worthily, while existing solutions from the literature have been committed towards optimization of end-user DR efforts using chatbot technologies, these attempts solely focuses on specific asset use cases and are therefore less adaptive to encompass the broader scope of microgrid modelling of DT asset for demand side recommender scheme based on chatbot augmentation. In contrast to these state-of-the-art studies, this study attempts to provide solution to the aforementioned gaps by modelling individual end-user electricity asset towards prediction of consumption profile while generating of actionable recommendation. Furthermore, users can interact with chatbot to further clarify recommended tips to obtain real-time information. As such, this study focus on answering queries such as. How would conversational chatbot technology improve the performance of demand side recommender scheme based on integration of DT of individual electricity asset?

To answer this question, this study presents an ensemble of demand side recommender chatbot and improved behavior prediction and scoring schemes using hybrid DT model of individual smart grid asset and PageRank models. Given the mentioned underpinning technologies, an empirical study explores the role of demand side conversational chatbot on improving end-users potentials for extended engagement with energy efficiency schemes. Variables (i.e., dwell time, mouse click, etc.) were selected to validate the correlation between improvements in users' engagement index and introduction of demand side conversational chatbot based on the hypothesis that there are relations between extended consumer engagement with DR schemes and the deployment of demand side recommender chatbots.

A. *Key contributions:*

The major contributions of this study are:

- The study presents a proof of concept of GPT based conversational chatbot interface for extending demand side recommender system's consumer engagement.
- Integration of hybrid DT model of individual end-user electricity asset enhanced with domain-specific physical constraints/laws towards facilitating atomic level analytics/feedback and individual assets' level interaction using proposed conversational chatbot.

II. HYBRID DIGITAL TWINS MODELLING OF SMART GRID ASSET

In this section, the hybrid digital twins was developed for the prediction of end-user assets' behavior. The proposed hybrid model comprises of the blackbox recurrent neural network (RNN) model (see equation (3)) and a whitebox physics model description of energy assets' behavior (equations (1), (2)). An example use case of selected microgrid asset such as *Solar PV* and *HVAC* airfilter were considered and described as follows.

A. *Solar PV physics*

The output power of the solar photovoltaic is modeled as.

$$P_{pv} = \eta S_{\varphi}(1 - 0.005(T_a + 25)). \tag{1}$$

Here, η is the PV conversion efficiency, T the cell/ambient temperature and S represents PV system surface area. Parameters (η, φ, S, T), keenly determines the quantity of power extracted from the solar irradiation φ.

B. *HVAC airfilter physics*

The description of HVAC air-filter model based on relationship between filter fan power consumption, estimation of filter efficiency and air quality as per measured outdoor air concentration subject to filter clogging is given as.

$$m = Q_v \nabla t(C_r - C_s)\,[\mu g] \tag{2}$$

where m is the mass accumulated in the filter at every time step t. C_s is the supply air concentration while C_r is the room homogeneous air concentration. The outside air flow rate is denoted as Q_v and V represents the room volume.

$$y(t) = f(y(t-1)), y(t-2), \ldots, y(t-d_y)) \tag{3}$$

Here, y represents the historic energy demand acquired over time (t), and the lagged output feedback is represented by d_y.

III. BEHAVIOR SCORING FOR RECOMMENDER CHATBOT

PageRank algorithm is used for scoring predicted individual DT asset profile (described in Section II) towards recommendation provision and conversational chatbot engagement for DR services provision.

A. Graph based behavior scoring

$$\mathrm{PR}(V_i) = (1-d) + d\sum_{i=1}^{N}\frac{\mathrm{PR}(V_i)}{N(V_i)} \tag{4}$$

Here N denotes the total number of nodes, d represents the damping factor, and $\mathrm{PR}(V_i)$ is the currently ranked asset consumption profile.

We retained the top-N recommendation structure to give users a brief of the efficiency tips required to optimize their energy profiles. This is further enhanced using the conversational chatbot to extend their knowledge about the energy system.

B. Chatbot technologies:

To achieve the proposed chatbot, an opensource OpenAI model termed generative pretrained transformer 3 (GPT-3) was deployed to foster interaction between the developed hybrid DT and electricity end-users. Large-language models such as OpenAI's GPT-3 are built to imitate human language reason being that they are trained on vast amount of examples obtained from the internet. In our case, outputs of the recommender systems serves as input data/prompts [14] which connects directly with the chatbot and the user can continue discussing to further clarify the suggested advice. GPT-3 is built on transformer neural network comprising of transformer decoder layer consisting of feed-forward neural network (see equation (6)), encoder and self attention. The outcome of self attention was obtained as the sum of the product of input text vector and its score. Multi head Attention [15] mechanism connects the encoder and decoder. The encoder maps a set of input vector representation $(x_1, ..., x_n)$ into a continuous representation sequence z $(z_1, ..., z_n)$. The decoder generates an output signal $(y_1, ..., y_n)$ an element at a time given sequence z. The model is auto-regressive at each step and consumes previously output symbol as additional input towards producing the next symbol. The overall architecture of the transformer follows this scheme based on stack on self-attention (see equation (5)) and encoder-decoder fully connected layers of point-wise encoder and decoder network

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V, \tag{5}$$

where the attention function is computed as a set of queries which is simultaneously packed together as matrix Q while the key and value is packed into K and V matrices. d_k is the dimension of keys.

$$FF(x) = \max(0, xW_1 + b_1)W_2 + b_2 \tag{6}$$

Here, $FF(x)$ represents the feed-forward neural network, x is the input vector that is multiplied with the specific weight resulting into weighted input, b is a constant value termed as bias.

Intent modeling: Intent analysis is used to trigger an associated response from the chatbot which helps to further clarify advice presented to end-users. For example, when the recommender system suggests "Save energy by changing HVAC filter", intent analysis based on key-wording spotting and synonyms identification triggers words like "HVAC", "filter" and "save-energy" which helps conventional chatbot to be customized to better suite end-user needs [16].

C. Evaluation metrics

The formal description of the evaluation metrics for developed DT models is expressed in Table I. Additional system evaluation using consumer engagement index was considered. Customer engagement scores for demand side recommender chatbot was computed as a ratio of the total independent consumers engagement with top-N advice to the total number of advice received by consumers in the period under review (description in equation (7)). Again, this metric determines the potential likelihood of a consumer extending their engagement with the proposed framework. Engagement index (EI) is adopted metric for formalising consumer engagements. EI is computed as follows

$$EI = \frac{R}{A \times T} \times 100, \tag{7}$$

where R is the total number of user reactions to advice for analyzing period T and A is the total number of advice.

As a main objective is to evaluate consumers engagements inferred from collection of user behavior feedback/dataset defined as follows [17]:

1) Dwell time dataset was used as proxy towards consumer engagements.
2) Mouse click.
3) Conversational chatbot engagements.

TABLE I: Mathematical equation of valuation metrics

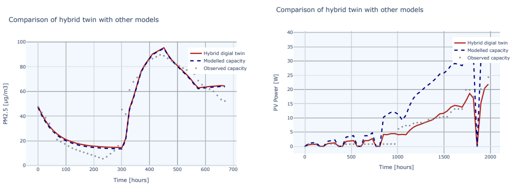
Metrics	Equation
Root mean squared error (RMSE)	$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2}$
Mean squared error (MSE)	$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2$

Here, p_i is the estimation of deliberate information while q_i is the actual value of information within of N period.

IV. Numeric results

This section describes the results of the experimentation. Modelled selected top-N microgrid (MG) assets (i.e., comprising of generator and loads) were used in prediction of future assets' profile towards ranking and recommendation provision. The data basis for the experiment was obtained from number of sources which covers the following technologies: solar PV, battery, HVAC filter etc. The dataset that facilitate modelling of HVAC system was obtained from Airparif [18], while solar PV dataset was sourced from [19].

Figure 1 (a) is a comparison of developed HVAC indoor air quality hybrid DT, sensor data observation and the baseline physics model towards ranking/recommendation. It is worthy of note that the air filter plays important role in HVAC system



(a) Comparison of the hybrid digital twins, observation and physics model for HVAC air quality with a 670 hours time-range

(b) Comparison of the hybrid digital twinsc, observation and physics model for solar PV with a 1800 hours time-range.

Fig. 1: Comparison of the baseline physics model and the proposed hybrid DT with sensor data observation of selected microgrid assets

due to its ability to ensure protection of equipment/residents from airborne pollutants. Blockages of HVAC filter due to deposited PM2.5 mass can result into increased electricity consumption. Similarly, Fig. 1 (b) is a depiction of comparison of solar PV baseline physics model and the proposed hybrid DT with sensor data observation. Result from Table V illustrates a comparison of the performance of valuation metrics (MSE and RMSE) between the physics (baseline) and proposed hybrid DT framework for selected microgrid assets (i.e., Li-ion, HVAC airfilter). For example, the hybrid DT of HVAC air filter achieved about 84.13% decrease in MSE (from 44.929 to 7.1294 units) when compared to baseline scenario.

TABLE II: Descriptive statistics of chatbot in increasing recommendations click rate and the number of advice clicked by consumers

	Recommendation tips		Chatbot		% Increase
	Mean	Std.	Mean	Std.	
# Click	7.545	3.115	12.727	3.250	68.675
# Dwell-time	1.175	0.661	3.877	1.491	228.077

TABLE III: Participant demographic characteristics.

Age	20-24 (1, 7%)	25-29 (6, 43%)	Gender	Male	11 (78.60%)
	30-34 (4, 29%)	35-39 (1, 7%)		Female	3 (21.40 %)
	40-44 (1, 7%)	44-49 (1, 7%)			

TABLE IV: Engagement index (EI) of chatbot and recommender system based on consumers click rate

	Recommendation tips	Recommendation + Chatbot	% Increase
EI	34.583	58.333	68.675

End user interview and observations: An end-user study was performed to understand the impact of demand side recommender chat-bot on recommendation provision and stakeholders (i.e. end consumers) engagement with the demand side recommender framework. To achieve this, We collected data associated with recommendation prompts attributed to number of MG assets. Further more, we recruited 14 participants (Ages between 20-50) who are resident of the Tallinn university of technology, Cybernetic building to participated in the study. A randomly sampled top-N efficiency recommendation prompts for engaging recommendation chat-bot were sampled and presented to each participants. User behaviors around these recommendation prompts (baselines) were compared against corresponding posts from conversational chat-bot to validate the system. Table III shows the demographic characteristics of participants comprising of age and gender. Participants are required to provide answers to the following (three) questions:

- Q1: Will you click the recommendation prompt after seeing the advice prompt?
- Q2: Will you click the recommendation prompt after being aware of DR recommendation chat-bot?
- Q3: Which recommendation prompt is most attractive for engaging the DR recommendation chat-bot?

The use of questionnaire was was further augmented by other usability methods such as selected user study [17] evaluation methods comprises online (live user studies i.e. click-through rates (CTR)) and offline (explicit rating) approaches for conversational recommendation chatbot engagement performance validation. The user-centric evaluation approach [17] deployed was based on user specific conversation with electricity asset chatbot. Important/key parameters for estimating user behavior includes click-through rates (CTR) and the dwell-time rates.

The summary of the results of measured user characteristics is presented in Table II. As revealed by this result, there was about 68.7% increase in click rate and 228% increase in user dwell-time when interacting with the chat-bot based recommendation prompts which encourages end-consumers to read more and further engage the framework. Table IV describes outcomes of EI with recommendation chatbot. Results revealed about 69% increase in users engagement with efficiency recommendation tips compared to baseline scenario.

Statistical significance test: The result of this analysis revealed that the value of t-statistics (-3.19921) and p-value of p=.00497 significantly support the hypothesis that the conversational chatbot enhance consumers engagement with demand side recommendation scheme. Statistical significance

TABLE V: Hybrid vs. physics twins of electricity assets

	Asset	MSE	RMSE
Physics-baseline	HVAC	44.9290	6.7030
Hybrid DT		7.1294	2.6700
Physics-baseline	Li-ion	0.1220	0.3493
Hybrid DT		0.0003	0.0169

TABLE VI: End-consumer scored overall load profile

Load profile	Peak	Mid	Base
Avg. Pagerank score	1.000	1.140	0.845

outcome of $p < 0.5$ revealed the strong influence of the chatbot in improving user engagement with the proposed demand side recommendation scheme.

Table VI describes the score associated with overall end-user consumption profile towards recommendation provision using equation (4). Result indicate prevalence of mid load profile (0.140 score) compared to either peak or base load, suggesting possibilities for downward review of end-user energy behavior towards base load profile. Table VII is an illustrative example of top-N efficiency recommendation prompt provision targeting individual end user assets.

TABLE VII: Illustrative example of top-N efficiency recommendation

Asset ID	Recommendation tips	Predicted score
BAT_R 1	Install battery storage to achieve up to 42% reduction in electricity demand	0.471289
REC	Change HVAC filters to save up-to 30% energy	0.453100
BAT_R 2	Operate/Charge battery at optimal temperature 25°C to protect the battery and reduce demand	0.42588

A. Application integration:

The final application in Figure 2 was based on the integration of recommendation tips (see Table VII) and NLP based chatbot interface that facilitates further recommendation clarification based on developed standard interface.

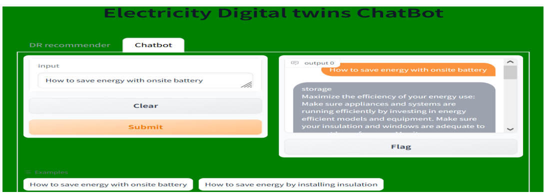


Fig. 2: Illustrative example of conversational agent dialogues between consumer and chatbot based on efficiency recommendation prompts [14] .

V. Conclusion and Discussion

This paper presents a novel a demand side recommender conversational chatbot that helps non-technical electricity end-user enhance decision-making capabilities for DR operations using behavior prediction of hybrid DT twins of individual electricity assets and conversational chatbot which dynamically extends the functionality of demand side recommender system. Specifically, the study presented a case study based on application of GPT-3 chatbot that helps consumer further their understanding about recommended energy efficiency tips.

Feasible study challenge includes inability of chatbots based on current state of technology to totally replace human agents in key service interactions as there is possibilities to fall-short while resolving complex end-users' complaints.

Future efforts will be directed towards expanding the number of addressable models to integrate key electricity grid assets.

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Appendix 9

IX

K. Nosrati, S. Alsaleh, A. Tepljakov, E. Petlenkov, A. E. Onile, V. Škiparev, and J. Belikov. Extended reality in power distribution grid: applications and future trends. In *Proceedings of 27th International Conference on Electricity Distribution (CIRED 2023)*, volume 2023, pages 3615–3619, 2023

EXTENDED REALITY IN POWER DISTRIBUTION GRID: APPLICATIONS AND FUTURE TRENDS

Komeil Nosrati*, Saleh Alsaleh, Aleksei Tepljakov, Eduard Petlenkov Abiodun Onile, Vjatšeslav Škiparev, Juri Belikov
Department of Computer System Department of Software Science
Tallinn University of Technology – Estonia
*komeil.nosrati@taltech.ee

ABSTRACT

Modern automation schemes have substantially improved by using standard communication protocols, upgraded technologies and user-friendly tools in power distribution domain. Nevertheless, this fundamental functionality of modern smart grid is violated when it occasionally interferes with the execution of error-prone supervision, control, and maintenance operations. In light of these practical problems, this study reviews the state-of-the-art applications of extended reality (XR), as an advanced enough visualization technique in electricity distribution, which can contribute functional solutions in four different domains protection and control, training, safety enhancement, and energy management system. This technique not only reduces the operational costs and enables more precise decision-making but can also improve the overall safety and training standards in the distribution sector and open new opportunities for future sustainable power distribution.

INTRODUCTION

Through the application of modern processing, visualization, and motion tracking technologies, virtual reality (VR) allows for an unparalleled level of human-machine and human-human interactions [1]. A variety of hardware including head-mounted displays (HMDs), cubic immersive spaces, computer devices associated with other complemented tools simulating and tracking process can be used to deliver VR experiences and transport the user into a virtual world [2]. Augmented reality (AR) is a distinguished type from VR, in which additional sensory data in real world is superimposed on the virtual world using digital devices to enhance the inter- active ability and the perception of reality based on computer- generated information [3]. Mixed reality (MR), characterized by the combination of AR and VR areas, is acknowledged as the upcoming development in how humans interact with technology and the environment and how manufacturing and production industry will be transformed [4].
The fourth industrial revolution has already been witnessing plenty of applications of VR/AR/MR-commonly referred as VAM or extended realities (XR) [5]. These different terminologies have been used inconsistently by academics and professions resulting in conceptual ambiguity [6]. The work [7] organized these various terms in a systematic framework. The authors concluded that (i) XR does not imply extended reality, but a more open strategy where X denotes an unknown variable: xReality [8]; (ii) two fundamentally different AR and VR should be considered as distinct experiences [9]; (iii) AR and VR experiences can be categorized along a continuum ranging, from assisted to MR and atomistic to holistic VR, respectively [10]. However, we invite readers to be cautious of using these interchangeability words employed for XR technologies.
The works [11] and [12] respectively conducted a thorough review of the AR and VR from a general point of view. There are also some articles providing an overview on reality applications from the different perspectives of manufacturing industry [13], robotics [14], medical visualizations [15], 3D modelling and design [5], professional training [16] and learning [17], tourism management [18], and maintenance services [19], which can be categorised in four prototypical views, MR-dominant, VR-dominant, MR-centred views (which are academically driven), and XR view (which is informed by industry). For both academics and industry to benefit from the new reality field, a consolidated framework has been organized in which XR is an umbrella term with AR and VR in its sub streams outlined in Figure 1.
For now, XR is still under development and needs further investigations. While some considerable research and studies have been conducted on reality applications in various disciplines, there has been no review of how XR can be integrated into the power systems in the current operation and control framework. Hence, we address this gap by detailing a comprehensive review of the XR applications in electrical distribution and summarizes how this technology fuses with the existing operation and control schemes through the lenses of industry, academia, and the user. Compared with other review papers on reality applications, the main merits of this manuscript include:

- Plotting a grid visualization research map from control, training, safety, and energy management (EM) views.
- Exploiting the modularized technique in Figure 1 to dive into the fundamental units of power distribution.
- Discussing challenges and future trends associated with adopting XR in power distribution grid.

Our research provides the state-of-the-art applications of XR in distribution level, which can contribute functional solutions in various domains and opens new opportunities for future sustainable power distribution.

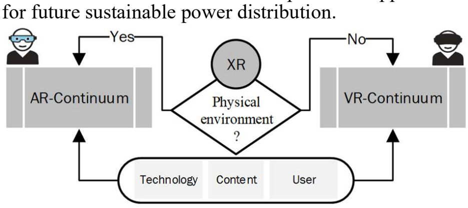

Figure 1: XR framework.

PROTECTION AND CONTROL

In distribution sector, the given tasks from substations to the loads can be remotely monitored and managed by using SCADA system over standard communication protocols (e.g., IEC 61850). Notwithstanding the recent progress in SCADA systems, the isolation of automation data from the environment causes the process of applied visualization technique (e.g., HMI), data management, control, and maintenance operations to be slow and error prone. Thanks to the development of XR visualization methods, real-time interaction between operator and distribution equipment and virtual objects will be enabled. As an alternative to the single-line diagram (SLD), a static augmented area was proposed in substations [20], where the operators were equipped by AR to interpret, monitor, and manipulate data measurements without displaying of dynamic events. In [21], a robust technique was proposed to create augmented area using VR and the concept of natural markers, which allows a tele-operation task in substations.
Together with standard protocols in communication system, the work [22] deployed the AR visualization technique for SCADA data to facilitate human-based activities in substations (see Figure 2). This solution not only could enable the automation data to be visualized near the equipment, but also, using full 3D models and animated widget, it could help the maintenance engineers to cope with their tasks in an effective way. Also, [23] integrates the VR with the feeder protection relay in which provide a foundation to reach a versatile and multiple test strategy for substation control and protective virtual devices, which allows to examine essential protection schemes with a lower cost. In demand side, [24] proposed a remote-control system for electric household appliances using AR and digital twin (DT) in which on-off and control operations could be accomplished remotely in real time. Table 1 shows XR overview applications in control part.

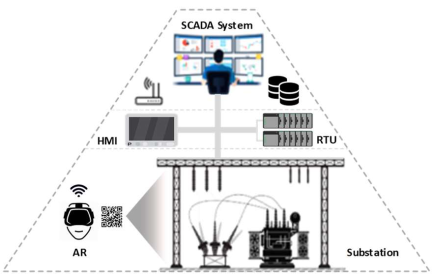

Figure 2: AR based control through SCADA in substation.

Table 1: XR for control of power distribution grids.

Paper	Method	Description	Area
[20]	AR	Static augmented for data measurements in panoramic view	Substation
[21]	VR	Robust technique of augmented area for tele-operation tasks	Substation
[22]	AR	Visualizing the SCADA data to facilitate human-based activities	Substation
[23]	VR	Virtual feeder protection relay	Substation
[24]	AR	Enabling a remote-control system for electric household appliances	Load side

TRAINING

In power distribution networks, operators and maintenance workers need hands-on experiences to effectively deal with this continually changing environment. However, due to the complexity and hazards of middle-voltage electrical networks, hands-on training in all possible field scenarios without risking the networks or trainers is challenging. Simulation-based training not only protects participants and equipment, but also can provides the operators with a wide range of conditions and unexpected events that either rarely occur or are unsafe to recreate on a physical power network. The work [25] proposed a realistic virtual substation training environment architecture, where the Coloured Petri Nets (CPN) models govern the components behaviour in a 3D substation environment.
In the non-immersive VR simulations, trainers only use the mouse and keyboard, and see 2D displays, limiting visual immersion. Modern technology has enabled researchers to create viewing devices for virtual environments with intuitive input. Researchers in [26] proposed a substation training system using a 6-DOF mouse and stereoscopic display system. The 3D mouse lets users move in 3D space, while the stereoscopic display system improves 3D perception. In [27] and using the leap motion device (LMD) for operator, the interaction was improved by 3D tracking of user's hand and performing more intuitive actions. Also, by deploying an immersive VR experience based on HMDs, where the user's view reacts to head movements, giving the impression of being transported to a new environment, a substation was simulated in [28].
The success of the virtual training environment is not restricted to the interaction and visual impression levels alone. Using 3D models, scenarios, and scripted events, [29] proposed comprehensive power system safety training for offshore oil platform power systems. The immersive HMD and controllers enhanced storytelling to organize and present training information. Due to auditory and haptic feedback, human preferences, and tracking system accuracy, measuring, and correlating the effects of such settings is difficult. By surveying electrical utility industry workers, researchers in [30] sought to improve an immersive VR training application by using an elbow connection manoeuvre in an underground transformer. Via the Cave Automatic Virtual Environment (CAVE) system, which allows a shared virtual area, a VR based substation training area was given in [31] with high acceptability, and potential for improvements in usability and visualization. Table 2 shows an overview of XR based training.

Table 2: XR training overview in power distribution grids.

Paper	Method	Description	Area
[26]	VR	Improved interaction and visual immersion using 3D systems	Substation
[27]	VR	Natural hand interaction by LMD	Lines
[28]	VR	Immersive training areas by HMD	Substation
[29]	VR	Storytelling for training content of immersive VR area	Operation
[30]	VR	Evaluation of HMD based immersive VR training areas	Operation
[31]	VR	Evaluation of CAVE based immersive VR training areas	Substation

SAFETY ENHANCEMENT

Improvements in protective devices and wiring methods in accordance with recent standards have all led to greater levels of electrical safety. However, the inherent dangers of using electricity will always exist and will be a serious issue for electrical services in distribution sector. Hence, it is vital to go beyond the conventional methods and exploit new VAM reality-based techniques to guarantee the safety in this sector where risks and accidents are unavoidable. Towards this, a prototype simulator to support safety awareness in construction industry is outlined in [32]. Also, a prototype desktop VR model to improve the safety and design in the built area is developed in [33]. This model has the potential to serve as a virtual safety manual for the public, a designing tool for distribution companies and educational tool for trainers.

In operation and maintenance process, AR technology can work as an electronic fence for safety warning in distribution sites where a tracking technology of simulation localization and mapping (SLAM) is used for visual warning of risks and keep the operators vigilant [34]. By following the idea of decreasing the error rate in the operational sites such as electrical substations and transmission networks, the works in [35] and [36] deal with implementation of tasks (e.g., changing and installing devices such as circuit breaker, electro-mechanical machines, and so forth) through some functionalities which follow a series of instructions. This not only ensures secure, correct, and complete performing of instructions, but also considers the accessibility and needed information according to the workers expertise to accelerate the overall procedure. An overview of XR applications in safety enhancement is presented in Table 3.

Table 3: XR overview for safety in power distribution grids.

Paper	Method	Description	Area
[32]	VR	A simulator which can highly support electrical safety awareness	Load side
[33]	VR	Desktop VR to navigate a virtual area and interact with electric tools	Load side
[34]	AR	SLAM tracking technology for risk visual warning	Operation
[35],[36]	AR	Safe installation of electric devices	Operation

ENERGY MANAGEMENT SYSTEM

Inadequate data-driven uncertainty planning/visualization and decision-making (DM) schemes are two challenges in smart grids which can be addressed by XR solutions. Research in XR has benefited immensely from IT development associated with the advent of the smart grid including data capturing technologies, IoT, wireless sensor networks, mobile hardware, GPS, and other associated technologies [37]. Visualization technique has been considered as the weak links in EM schemes, however, it requires additional changes to remain relevant with increasing integration new generations. The work [38] revealed that one of the major challenges impeding deployment of advanced analytic models (such as DTs solution) for the smart EM systems includes unavailability of VR and integrated dynamic simulations technologies. A holistic approach will be required for developing/attaining such system that accommodates integration of autonomous and transient operation, management, etc. Questions remains about how to effectively present information to energy stakeholders to improve DM skills [37].

Coupled with graphical techniques, VR based EM solutions has significant potentials to improve the efficiency of demand response programs [39] (see Table 4). One key limitation of traditional methods is that they fail to incorporate consumers interaction with 3D energy area. By extending EM visualization from 2D into 3D, [40] showed the possibilities for new services and products targeting EM. To test the XR-based interface, a physical testbed was developed to boost the user's intuition and energy awareness [41]. This allowed for virtualization of the actual world and virtual information in real time and enabled the user to intuitively determine real-space information. In [42], intelligent financial information was given to understand the market events in energy sector. Furthermore, the study in [43] presented three VR-based visualization methods to intuitively visualize the energy flow. As a case study, we have conducted an experiment on this matter in the CS laboratory at Tallinn University of Technology [3],[44]. As seen in Figure 3, an XR-based interface for HVAC air filtration system using DTs prediction was tested by an operator. Associated with physics, data-driven based model and DT predictions, actionable recommendations based on generated scores by Pagerank algorithm (see Table 5) have been considered in the HMD device to enhance end-user EM potentials.

Table 4: XR overview for EM system.

Paper	Method	Description	Area
[40]	VR	An interactive energy visualization	Building
[41]	AR/VR	Energy demand management based on real-time visualization	Building
[42]	VR	A design prototype to visualize the financial data	Energy Sector
[43]	VR	Energy visualization in an intuitive manner	Electric Device

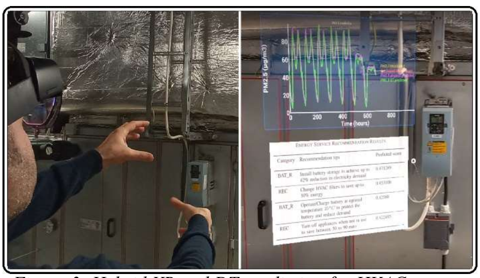

Figure 3: Hybrid XR and DT prediction for HVAC system.

Table 5: Energy service recommendation results.

Category	Recommendation tips	Score
BAT_R	Install battery storage to achieve up to 42% reduction in electricity demand	0.471
REC	Change HVAC filters to save up-to 30% energy	0.453
BAT_R	Operate/Charge battery at optimal temperature 25°C to protect the battery and reduce demand	0.426
REC	Turn off appliances when not in use to save between 50 to 90 euro	0.423

DISCUSSIONS AND FUTURE TRENDS

For a sustainable distribution grid operation, a reliable and safe infrastructure, as well as applicable control methods with proper training strategies, is essential. To enhance the reliability, XR can contribute functional solutions. To achieve these, virtual schemes should be fused with the existing operation and control schemes with respect to the design complexity and costs. Based on these explanations, there are some fundamental discussions on XR based strategies for distribution grids, as follows.

- ***Protection and control:*** Towards more reliable control of grids, digital models can be exploited using XR to simulate real world scenarios. Developing a software platform under accepted communication standards not only can provide an adaptive workflow approach to make control tasks more accessible, but also other grid components can be integrated into the application. Also, XR can be deployed for virtual commissioning in which debugging of control system (e.g., RTU) can be performed before fusing to the actual system.
- ***Safety:*** As power distribution networks get smarter, they are also able to get safer. In this regard, the XR technology has an exceptional potential in practical safety improvement by fusing (i) a remainder of safety standards; (ii) online monitoring of safety elements; (iii) heads-up alerts; and (iv) quick references of operating practices in a safe mode and without making any assumption into the future XR based distribution grids.
- ***Training:*** To grow the XR application beyond the existing hand-engineered scenarios, DTs can be employed to control the behavior of the training environment's components. Also, the abundance of tracked motion data and performance metrics inside the XR training area may be utilized to infuse this area. Finally, while VR environments now dominate training applications, there is promise for AR and MR to assist with on-site training in future.
- ***Energy management system:*** Future research directions of XR applications for EM will be further enhanced by deploying of technologies such as DTs, e-commerce energy recommendation models, and fusing interactive real-time methodologies to the current techniques.

CONCLUSION

We present an exhaustive review of XR visualization technique in distribution grid in four different domains. For all domains discussed in this study, the modularized technique of XR framework is exploited to dive into the fundamental units of power distribution. Also, some recommendations are identified regarding fusion of distribution grids with virtual schemes. In addition, despite the efforts directed in this area, new research lines and open questions (summarized in Table 6) concerning the reliability improvement of grids operation with modern XR-based visualization approaches are still raised.

Acknowledgments

The work was partly supported by Estonian Research Council grants PRG658 and PRG1463. The work of K. Nosrati, S. Alsaleh, A. Onile and V. Skiparev in the project “ICT programme” was supported by the European Union through European Social Fund.

Table 6: Open questions and challenges.

Domain	questions
Control	How will develop a general software platform for XR applications in the designed control systems of the grid under existing communication standards? How can XR be deployed for virtual commissioning process before fusing the designed control system to the actual system?
Safety	What strategies can be exploited by XR to protect the grid elements in a safe mode without any assumption?
Training	Which new approaches (such as intelligence and data-driven techniques) can be adjusted to the trainees' different levels of competence and learning styles? What will be the performance of this strategy?
EM	What policies can be implemented now to enhance XR applications for EM by deployment DTs and e-commerce energy recommendation models? Can real-time and interactive algorithms in XR help energy stakeholders to improve their DM skills?

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Curriculum Vitae

1. Personal data

Name	Abiodun Emmanuel Onile,
Date and place of birth	1 January 1988 Osun state, Nigeria
Nationality	Nigeria

2. Contact information

Address	Tallinn University of Technology, School of Information Technologies, Department of Software Science, Akademia tee 21B, 12618 Tallinn, Estonia
Phone	+372 53676853
E-mail	abiodun.onile@taltech.ee

3. Education

2013–. . .	Tallinn University of Technology, School of Information technology, Software science, PhD studies
2014–2016	University of Bedfordshire, Faculty of science, Embedded systems engineering, MSc *cum laude*
2007–2012	Ladoke Akintola University of Technology, Faculty of Engineering, Computer science and engineering, BTech

4. Language competence

Yoruba	native
English	fluent

5. Professional employment

2020– . . .	Tallinn University of Technology, Estonia, doctoral student-junior researcher
2016–2019	Elizade University, Ilara-Mokin, Nigeria, Lecturer II
2013–2014	Niger State Development Company, Nigeria, ICT Institute trainer
2011–2012	Philips, IT Staff (Network Monitoring Services)

6. Voluntary work

2002–2003 Unicef Peer Educator, UNICEF

7. Computer skills

- Programming languages: Python, C#, C++ and Java programming languages

8. **Honours and awards**

- 2013, Merit Scholarship Award, University of Bedfordshire, United Kingdom
- 2019, Dora Plus scholarship for PhD students' mobility
- 2021, Faculty of Information Technologies, Tallinn University of Technology, best paper award

9. **Defended theses**

- 2016, Primate behaviour classification using machine learning algorithm, MSc, supervisor Dr. Benjamin Inden, University of Bedfordshire, School of Computer Science and Technology
- 2012, Design and development of Wireless sensor network for farm monitoring, supervisor Dr. Rafiu Adesina Ganiyu, Ladoke Akintole university of technology, Department of computer science and engineering

10. **Field of research**

- Demand side management
- Demand side recommendation services
- Industry 5.0 Digital twins
- Physics informed machine learning
- Smart grid

11. **Scientific work**
Papers

1. A. Navon, R. Machlev, D. Carmon, A. E. Onile, J. Belikov, and Y. Levron. Effects of the COVID-19 pandemic on energy systems and electric power grids—a review of the challenges ahead. *Energies*, 14(4), 2021
2. A. E. Onile, R. Machlev, E. Petlenkov, Y. Levron, and J. Belikov. Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. *Energy Reports*, 7:997–1015, 2021
3. A. E. Onile, J. Belikov, Y. Levron, and E. Petlenkov. Energy efficient behavior modeling for demand side recommender system in solar microgrid applications using multi-agent reinforcement learning model. *Sustainable Cities and Society*, 90:104392, 2023
4. O. Ogidan and A. Onile. Automatic recognition and classification of medicinal plants: A review. In *The Therapeutic Properties of Medicinal Plants*, pages 271–284. Taylor & Francis Group, 2019
5. D. Akinyele, O. Babatunde, C. Monyei, L. Olatomiwa, A. Okediji, D. Ighravwe, O. Abio-dun, M. Onasanya, and K. Temikotan. Possibility of solar thermal power generation technologies in Nigeria: Challenges and policy directions. *Renewable Energy Focus*, 29:24–41, 2019

6. O. Ogidan, A. Onile, and O. Adegboro. Smart irrigation system: A water management procedure. *Agricultural Sciences*, 10:25–31, 01 2019

7. O. Z. Oshin, A. Onile, A. Adanikin, and E. Fakorede. Reliability of distribution networks distribution networks in nigeria: Ikorodu, lagos state as a case study. *International Journal of Engineering and Emerging Scientific Discovery*, 3:10–33, 12 2018

Conference presentations

1. A. E. Onile, J. Belikov, and Y. Levron. Innovative energy services for behavioral-reflective attributes and intelligent recommender system. *In Proceedings of 2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe) – 10th International conference of IEEE PES ISGT Europe Conference, Virtual, The Hague, Netherlands, 2020*, 1(1):1–7, 2020

2. A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Applications of digital twins for demand side recommendation scheme with consumer comfort constraint. In *Proceedings of IEEE PES ISGT Europe 2023 (ISGT Europe 2023) – 13th International conference of IEEE PES ISGT Europe Conference*, 2023

3. A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Emerging role of Industry 5.0 digital twins in demand response electricity market and applications. In *Proceedings of IEEE PES ISGT Europe 2023 (ISGT Europe 2023) – 13th International conference of IEEE PES ISGT Europe Conference*, 2023

4. A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. A comparative study on graph-based ranking algorithms for consumer-oriented demand side management. In *Proceedings of 2021 IEEE Madrid PowerTech – 14th IEEE PowerTech*, pages 1–6, 2021

5. K. Nosrati, S. Alsaleh, A. Tepljakov, E. Petlenkov, A. E. Onile, V. Škiparev, and J. Belikov. Extended reality in power distribution grid: applications and future trends. In *Proceedings of 27th International Conference on Electricity Distribution (CIRED 2023)*, volume 2023, pages 3615–3619, 2023

6. A. E. Onile, J. Belikov, E. Petlenkov, and Y. Levron. Leveraging digital twins and demand side recommender chatbot for optimizing smart grid energy efficiency. In *Proceedings of 2023 IEEE PES Innovative Smart Grid Technologies - Asia (ISGT Asia) – 13th IEEE PES Innovative Smart Grid Technologies, Asia conference*, pages 1–5, 2023

7. D. Akinyele, L. Olatomiwa, D. Ighravwe, O. Babatunde, C. Monyei, and A. Onile. Evaluation of solar PV microgrid deployment sustainability in rural areas: A fuzzy STEEP approach. In *2019 IEEE PES/IAS PowerAfrica*, pages 593–598, 2019

8. A. Onile and O. Ogidan. A movement disorder recognition and analysis framework using non-contact and wearable sensors. In *IEEE NIGERCON 2017 Conference*, 11 2017

Elulookirjeldus

1. Isikuandmed

Nimi	Abiodun Emmanuel Onile
Sünniaeg ja -koht	01.01.1988 Osun state, Nigeeria
Kodakondsus	Nigeeria

2. Kontaktandmed

Aadress	Tallinna Tehnikaülikool, Tarvarateaduse Instituut, Akadeemia tee 21B, 12618 Tallinn, Eesti
Telefon	+372 53676853
E-post	abiodun.onile@taltech.ee

3. Haridus

2020–...	Tallinna Tehnikaülikool, Infotehnoloogia teaduskond, tarkvarateadus, doktoriõpe
2014–2016	Bedfordshire ülikool, Loodusteaduskond, Sardsüsteemide projekteerimine, MSc *cum laude*
2007–2012	Ladoke Akintola Tehnikaülikool, Inseneriteaduskond, Arvutiteadus ja tehnika, BSc

4. Keelteoskus

yoruba	emakeel
inglise keel	kõrgtase

5. Teenistuskäik

2020– ...	Tallinna Tehnikaülikool, Eesti, doktorant-nooremteadur
2016–2019	Elizade ülikool, Ilara-Mokin, Nigeeria, lektor
2013–2014	Nigeri osariigi arendusettevõte, Nigeeria, IKT mentor
2011–2012	Philips, IT tehnik (Võrgujälgimisteenused)

6. Vabatahtlik töö

2003–2003	koolitaja, UNICEF

7. Computer skills

- Programmeerimiskeeled: Python, C#, C++, Java

8. Autasud

- 2013, Merit stipendium, Bedfordshire ülikool, Suurbritannia
- 2019, Dora Pluss doktorantide mobiilsustoetustest
- 2021, Infotehnoloogia teaduskond, Tallinna Tehnikaülikool, parima artikli kaasautor

9. Kaitstud lõputööd

- 2016, Primate behaviour classification using machine learning algorithm, MSc, juhendaja Dr. Benjamin Inden, Bedfordshire ülikool, Loodusteaduskond
- 2012, Design and development of Wireless sensor network for farm monitoring, juhendaja Dr. Rafiu Adesina Ganiyu, Ladoke Akintole tehnikaülikool, Arvutiteadus ja tehnika instituut

10. Teadustöö põhisuunad

- Energiatarbimise juhtimine
- Energiatarbimise soovitus teenused
- Tööstus 5.0 digitaalsed kaksikud
- Füüsikapõhine masinõpe
- Tarkvõrk

11. Teadustegevus
Teadusartiklite, konverentsiteeside ja konverentsiettekannete loetelu on toodud ingliskeelse elulookirjelduse juures.

ISSN 2585-6901 (PDF)
ISBN 978-9916-80-219-9 (PDF)