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Research and Development of Quantification Methods for Aggregated Energy Flexibility

Freddy Plaum

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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 doctoral or equivalent academic degree.

Freddy Plaum

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Agregeeritud energiapaindlikkuse kvantifitseerimismeetodi uurimine ja arendamine

FREDDY PLAUM

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List of publications

The list of author's publications, on the basis of which the thesis has been prepared:

I **F. Plaum**, A. Rosin, and R. Ahmadiahangar, "Novel Quantification Method of Aggregated Energy Flexibility Based on Power-Duration Curves," IEEE Access, 2024, doi: 10.1109/ACCESS.2024.3461151.

II **F. Plaum**, R. Ahmadiahangar, A. Rosin, and J. Kilter, "Aggregated demand-side energy flexibility: A comprehensive review on characterization, forecasting and market prospects," Energy Reports, vol. 8, pp. 9344–9362, Nov. 2022, doi: 10.1016/J.EGYR.2022.07.038.

III **F. Plaum**, R. Ahmadiahangar, and A. Rosin, "Aggregated Energy Flexibility Provision Using Residential Heat Pumps," 2022 IEEE 16th International Conference on Compatibility, Power Electronics, and Power Engineering, CPE-POWERENG 2022, 2022, doi: 10.1109/CPE-POWERENG54966.2022.9880898.

IV T. Korõtko, **F. Plaum**, T. Häring, A. Mutule, R. Lazdins, O. Borščevskis, A. Rosin, P. Carroll, "Assessment of Power System Asset Dispatch under Different Local Energy Community Business Models," Energies 2023, Vol. 16, Page 3476, vol. 16, no. 8, p. 3476, Apr. 2023, doi: 10.3390/EN16083476.

V A. Shahid, **F. Plaum**, T. Korotko, and A. Rosin, "AI Technologies and Their Applications in Small-Scale Electric Power Systems," IEEE Access, vol. 12, pp. 109984–110001, 2024, doi: 10.1109/ACCESS.2024.3440067.

VI R. AhmadiAhangar, **F. Plaum**, T. Haring, I. Drovtar, T. Korotko, and A. Rosin, "Impacts of grid-scale battery systems on power system operation, case of Baltic region," IET Smart Grid, vol. 7, no. 2, pp. 101–119, Apr. 2024, doi: 10.1049/STG2.12142.

Author's contribution to the publications

Contribution to the papers in this thesis are:

I Freddy Plaum, as the paper's main author, was responsible for developing the concept of the proposed quantification method, the modeling, the simulations, and analysing the results.

II Freddy Plaum, as the paper's main author, was responsible for conducting the literature review regarding aggregated energy flexibility characterisation, quantification, forecasting, and market prospects.

III Freddy Plaum, as the paper's main author, was responsible for developing the concept for the publication, creating models and analysing the results.

IV Freddy Plaum, as the paper's second author, was responsible for developing models, performing simulations, and analysis of results

V Freddy Plaum, as the paper's second author, was responsible for conducting the literature review on small-scale electric power systems

VI Freddy Plaum, as the paper's second author, was responsible for conducting the literature review on the roles of grid-scale BESS in power systems

Abbreviations

aFRR	Automatic Frequency Restoration Reserve
AI	Artificial Intelligence
ARIMA	Autoregressive Integrated Moving Average
BaU	Business-as-Usual
BESS	Battery Energy Storage System
BRP	Balance Responsive Party
CC	Chance-Constrained
COP	Coefficient of Performance
DAM	Day-Ahead Market
DER	Distributed Energy Resources
DERA	Distributed Energy Resource Aggregation
DR	Demand Response
DSO	Distribution System Operator
EE	Energy Efficiency
EEC	Energy Efficiency Credits
ENTSO-E	European Network of Transmission System Operators for Electricity
ESC	Energy Savings Certificates
EU	European Union
EV	Electric Vehicles
EWH	Electric Water Heater
FCR	Frequency Containment Reserve
FF	Flexibility Function
GHI	Global Horizontal Irradiance
HEMS	Home Energy Management System
HVAC	Heating, Ventilation, and Air Conditioning
IDM	Intra-day Market
LFM	Local Flexibility Market
mFRR	Manual Frequency Restoration Reserve
MILP	Mixed Integer Linear Programming
NILM	Non-Intrusive Load Monitoring
NN	Neural Network
NOE	Nodal Operating Envelope
P2P	Peer-to-Peer
RC	Resistive-Capacitive
RES	Renewable Energy Sources
RR	Replacement Reserve
RtU	Right-to-Use
SOC	State-of-Charge
SVDD	Support Vector Data Description

SVM	Support Vector Machine
TCL	Thermostatically Controlled Load
TSO	Transmission System Operator
V2G	Vehicle-to-Grid
VRE	Variable Renewable Energy

1 Introduction

1.1 Background

The production, distribution, and utilisation of electricity are undergoing significant changes. Due to the growing concerns about global climate issues, the European Union (EU) has been promoting sustainable development in the energy sector. Since the introduction of the Renewable Energy Directive [1], the share of renewable energy sources (RES) in gross final energy consumption at the EU level has increased from 12.5% in 2010 to 23% in 2022 [2]. In Estonia, the share of RES in gross final energy consumption increased from 24.6% to 38.5% during the same period [3]. Initially, the Renewable Energy Directive had set the target of meeting 32% of overall energy needs with renewable energy by 2030. However, due to the rapid pace of clean energy transition, the target was increased in 2018 to 42.5% [4]. Furthermore, an ambitious goal has been set by the European Green Deal for Europe to become the world's first climate-neutral continent by 2050 [5].

The regulatory pressure to shift towards sustainable energy production has resulted in increasingly more Variable Renewable Energy (VRE) sources, such as wind and solar, being integrated into power. However, unlike traditional power sources, the generation of VREs is uncontrollable, stochastic, and challenging to predict. As a result of the growing employment of VREs, the grid operators face increasingly significant challenges to preserve grid stability as they must constantly balance energy supply and demand in order [6]. Absence of flexibility in a power network is characterised by fluctuations in voltage [7], [8], [9], frequency [10], and electricity price [11]. To address this challenge, additional innovative solutions are required, such as the utilisation of aggregated energy flexibility from energy storage systems, flexible loads [12], and demand response programs [13]. Grid-scale battery energy storage systems (BESS) play a crucial role in maintaining grid stability by offering ancillary services like frequency regulation, voltage management, and relieving congestion. Recent studies [Paper VI] on integrating BESS in the Baltic region have shown their capacity to improve power system flexibility, optimise energy distribution, and facilitate the incorporation of renewable energy sources. Leveraging these solutions would allow grid operators to supply energy efficiently and reliably while reducing the power sector's carbon footprint. However, it is challenging to supply more than 30% of annual demand using VRE at the present levels of energy flexibility [14].

The sources of energy flexibility may be roughly classified into two main categories: demand-side and supply-side flexibility [15]. Traditionally, power balance has been controlled from the supply side by modifying the output of power plants to adapt to variations in demand. Supply-side flexibility can be obtained by integrating power production units with varying response times into the power grid.

Demand-side flexibility sources include controllable loads in residential [16], commercial [17], and industrial [18] settings. Flexibility sources in residential buildings include appliances like electric heating systems, water heaters, refrigerators, dishwashers, washing machines, battery storage systems, and electric cars that may be controlled to some degree while still preserving user comfort. In commercial buildings, the heating, ventilation, and air conditioning system (HVAC) and lighting are significant consumers that account for around 74% of the electricity consumption [19]. These systems can be a good source of energy flexibility as they can be controlled within the regulatory bounds set for workers' well-being. Sources of flexibility in industrial loads are case-specific; for example, cold storage can be used as a source of flexibility in the food or fishing industry [18].

Due to the small scale of individual households, they may not provide enough flexibility to contribute to grid improvements or to participate in energy markets alone. Therefore, aggregation is necessary to build up a portfolio of smaller controllable loads that act as a more sizeable entity [Paper II]. Aggregators act as intermediaries between end-users and system operators, offering their combined flexibility to various energy markets such as wholesale, reserve, and ancillary.

At present, changes within households are occurring at a rapid pace; they are evolving into prosumers and forming communities that display similar behavioural patterns based on their geographical locations. A study [20] assessing the flexibility potential in Northern Europe, which includes Sweden, Denmark, Norway, Finland, Estonia, Latvia, and Lithuania, estimated it to be between 12 and 23 GW, or 15 to 30% of the region's peak consumption, thus highlighting the significance of this issue. Consequently, the flexibility potential of community microgrids in Northern Europe (hereafter: CMGs), comprising households as well as businesses and services, ranges from 8 to 19 GW, with households accounting for 3 to 13 GW of that total. Research indicates [Paper IV] that local energy communities can enhance their economic performance by over 10% by functioning as aggregators and delivering grid services directly to system operators.

1.2 Motivation

The existing electrical grids have been designed with a large focus on centralised power generation. However, grid management has become more challenging with the growing use of renewable distributed energy resources. To address these challenges, one potential solution is to utilise demand-side energy flexibility. Unfortunately, residential demand-side energy flexibility has not been fully utilised, as individual prosumers cannot provide enough capacity. An aggregator is required to manage demand-side energy flexibility. However, aggregators must use an appropriate quantification method to make informed decisions about utilising prosumers' energy flexibility in their portfolios. Therefore, this research was motivated by the current topical direction of research of developing appropriate methods for assessing the quantity of aggregated energy flexibility of residential electricity consumers. This PhD thesis aims to contribute to the existing literature by proposing a novel quantification method for aggregated energy flexibility based on the relationship between flexible power and the duration its activation can be sustained. The flexibility curves offer crucial insights for aggregators to make informed decisions about utilising their portfolios.

1.3 Aims, hypothesis, and research tasks

The main aim of this PhD research is to study and develop a novel method for quantifying aggregated energy flexibility of flexible devices in residential buildings, which will allow aggregators to gain better insights into how to utilise energy flexibility.

Hypotheses:

1. Quantifying energy flexibility using power-duration curves provides a more accurate and practical representation of flexibility compared to single-value metrics, offering insights into both short-term and long-term flexibility potentials.

2. Aggregated energy flexibility is asymmetric and non-linear, with different capacities for increasing and decreasing power and a non-proportional relationship between activation power and duration.
3. Asymmetry of energy flexibility potential impacts the grid stability differently, with demand increase showing more significant rebound effects.
4. Rebound effects in demand-side flexibility activations cause more significant changes to the demand profile than the flexibility activations themselves.

Research tasks:

1. Analysis of definitions, sources, aggregation process, and aggregation barriers for demand-side energy flexibility (Chapter 2).
2. Analysis of existing quantification methods of residential demand-side energy flexibility (Chapter 3).
3. Development of a novel method that quantifies energy flexibility using power-duration curves (Chapter 4).
4. Conducting a simulation-based case-study to illustrate the quantification process and showcase its strengths and weaknesses (Chapter 5).

1.4 Contribution and dissemination

This research contributes to advancing the understanding of energy flexibility in residential energy systems. The proposed methodology for quantifying flexibility through power-duration curves offers a novel and dynamic approach that addresses significant gaps in current methods. In contrast to static or single-value indicators, the approach developed captures the non-linear, asymmetric, and temporal characteristics of energy flexibility, presenting a thorough framework for both short-term and long-term applications.

The results of this thesis have been disseminated within academic and professional communities. Key findings have been presented at one international conference and have been published in two peer-reviewed journals, ensuring that the methodology and insights are accessible to a wider audience. The novelties of this thesis are as follows:

- Development of a power-duration curve approach as a new method for quantifying energy flexibility. This method offers a detailed and dynamic representation of flexibility over various time frames, providing a more nuanced overview compared to single-value metrics.
- The identification of asymmetric and non-linear properties of energy flexibility that challenge the traditional linear models of energy flexibility, providing a more accurate and comprehensive understanding, which is essential for improving demand response and load management strategies.
- The identification of the rebound overshoot phenomenon, where energy consumption starts oscillating after the rebound effect, which system operators would need to account for to maintain the balance.

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1.5 Application

Over the past ten years, there has been considerable growth in residential energy systems in Estonia, driven by the rising adoption of renewable energy sources and advanced energy technologies. During this timeframe, around 60 000 new residential dwellings were built. These buildings are outfitted with various energy systems, such as heating systems, water heaters, and sometimes battery storages, providing significant energy flexibility opportunities. It is essential to quantify the flexibility of these systems effectively.

The most significant energy-consuming devices in residential homes are space heaters and water heaters, accounting for approximately 60% and 20% of total energy use, respectively [21]. This illustrates the considerable flexibility residential loads could offer when integrated with smart control systems. Battery storage systems, which are becoming more prevalent in residential and commercial buildings due to their integration with rooftop solar panels, have the capacity to provide both short-term and long-term flexibility for maintaining grid stability.

Aggregators play a critical role in harnessing this flexibility. By pooling the flexibility potential from separate households and commercial structures, aggregators can generate a valuable resource for engaging in energy markets. For instance, if 50 000 residential units each provide 0.5 kW of flexibility during a demand response event, the total aggregated flexibility would reach 25 MW – enough to influence grid stability and the dynamics of energy markets significantly. In the context of Estonia, the flexibility provided by residential energy systems could greatly improve the ability to incorporate renewable energy into the grid. With manual frequency restoration reserve (mFRR) activations averaging 8.7 MWh during up-regulation events in 2022 [22], the possible contribution from residential systems could account for a substantial portion of this demand.

The power-duration curve method proposed in this research offers a strong tool for quantifying and optimising aggregated flexibility. By accounting for the dynamic, non-linear, and asymmetric characteristics of these energy systems, the method facilitates accurate forecasting and operational planning. It allows flexibility to be utilised efficiently, aligning the grid's requirements with the operational limitations of each system. Additionally, the rebound effects and asymmetric behaviours identified in this research emphasise the necessity for advanced methods, such as the power-duration curve, to ensure that flexibility is utilised both effectively and sustainably.

1.6 Thesis outline

The thesis is structured into three main sections. Chapter 2 offers a comprehensive analysis of the concept of energy flexibility, its sources, aggregation, and the challenges and barriers faced by aggregators. Chapter 3 provides an analysis of existing quantification methods highlighting the need for a more robust approach. In Chapter 4, a new quantification method based on power-duration curves is proposed and explained in detail. Chapter 5 presents case studies that quantify the energy flexibility of residential space heating, domestic water heaters, and battery systems. Finally, Chapter 6 concludes the thesis and offers recommendations for future research topics.

2 State of the art

As energy systems adapt to accommodate greater shares of renewable energy, the role of demand-side flexibility has become increasingly significant. This chapter offers a thorough examination of energy flexibility, its sources, and the challenges associated with its aggregation. It investigates the potential of various flexible resources, such as residential loads, battery storage, and electric vehicles, while also analysing the role of aggregators in utilising these resources for grid stability and market participation. The discussion highlights existing regulatory and market barriers, laying the groundwork for the subsequent analysis of flexibility quantification methods in the following chapter.

2.1 Characterisation of energy flexibility

2.1.1 Definition of energy flexibility

The concept of energy flexibility currently lacks a universally accepted definition. Various researchers have made efforts to define it within their respective fields of specialisation. Some researchers define flexibility simply as "*the ability to deviate from its reference electric load profile*" [23] or as "*the ability to reshape consumption patterns when interacting with the power grid*" [24]. More comprehensive definitions include "*DSF can be defined as the ability to strategically alter electricity usage by consumers (either commercial or residential) from their normal consumption profiles, by responding to control signals from grid operators and/or financial incentives from electricity generators/aggregators. The scope of these signals is to modulate and optimise electricity usage and to balance electricity production and consumption*" [25]. The IEA EBC Annex 67 project 'Energy Flexible Buildings' [26] has compiled an overview of the definitions of energy flexibility used by researchers in the literature, leading to the proposal of a general definition: "*The energy flexibility of a building is the ability to manage its demand and generation according to local climate conditions, user needs, and grid requirements. Energy flexibility of buildings will thus allow for demand-side management/load control and thereby demand response based on the requirements of the surrounding grids".*

2.1.2 Properties of flexibility

Flexibility services in the electrical grid refer to modifications in power generation or consumption that occur at a designated time, last for a specified period, and take place at a certain location within the grid. These services are characterised by several aspects, including whether they (a) increase or decrease power (direction), (b) the capacity of power adjustment, (c) when the adjustment begins, (d) how long it lasts, and (e) where it happens in the grid [27], [28], [29], as shown in Figure 2.1.

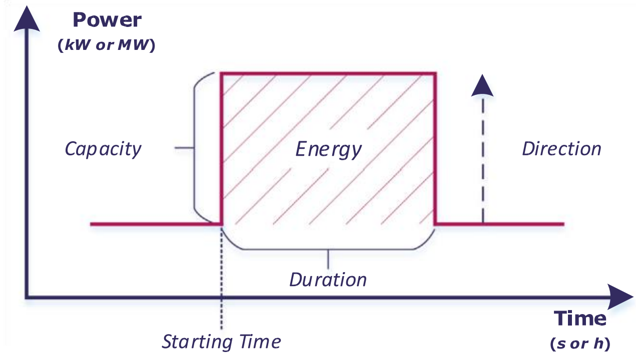

Figure 2.1. Properties of a flexibility service.

Additionally, other key attributes often discussed include how controllable and predictable these services are, their availability over time, the timing of delivery, and the associated costs or efficiency losses incurred by activating these services.

- The **directional property** describes the power flow direction of flexibility sources, distinguishing between those that consume energy and those that generate it. Flexibility sources may be unidirectional, either purely generating or consuming, or bidirectional, capable of both. Appliances like heat pumps, water heaters and washing machines, which only consume energy, are examples of purely consuming flexibility sources. Conversely, sources like PV panels and wind turbines, which generate power, are purely generating sources. There are also sources like battery storage systems and electric vehicles that are capable of both consuming and generating energy, thus classified as having bidirectional flexibility or being prosumer-capable loads.
- The **power capacity** attribute defines the power adjustment that a flexibility service can alter. When combined with the duration for which the flexibility service can be activated, flexibility sources can be classified as either capacity or energy type sources. Capacity type sources can be activated for a brief period with high power, while energy type sources can be activated for a longer duration but with lower power output.
- The **starting time** property refers to the delay between receiving the activation signal and the commencement of the flexibility service. Furthermore, certain flexible sources may only be activated during specific times of the day, either due to the owner's specifications or the inherent characteristics of the source.
- The **location property** describes the real position of the flexibility source in the distribution grid. For the distribution system operator (DSO), identifying the location where flexibility is required could be crucial for resolving congestion issues, whereas for the transmission system operator (TSO) and balance responsive party (BRP), the location holds less significance as their goal may simply be to balance generation and consumption [27].

2.1.3 Flexibility function

The Flexibility Function (FF) is a more complex characterisation method that can be employed to characterise energy flexibility controlled through penalty signals. Penalty signals are external control signals used by flexibility sources with penalty-aware controllers to adjust their demand. The consumer's incentive is to minimise their accumulated penalty. Depending on the purpose of controlling flexibility, penalty signals can represent different properties [30], such as:

- Real-time CO_2 emissions from consumed energy, where the flexibility controller aims to reduce overall carbon emissions, thus becoming emission efficient.
- Real-time electricity prices, where the objective is to minimise the total cost of consumption, thus achieving cost efficiency.
- If a constant penalty is in place, the flexibility controller will work to minimise total energy consumption and achieve energy efficiency.
- A penalty signal could consist of the mentioned elements combined, or it could be designed with different goals in mind, like decreasing peak power usage, addressing voltage and frequency issues, or managing grid congestion [31]; in such instances, the location of the utilised flexibility is also considered when creating a penalty signal.

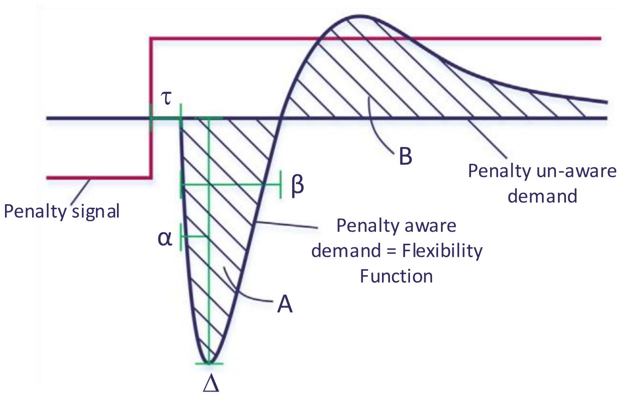

Figure 2.2. Flexibility Function depicting the expected response of energy flexible buildings.

FF was first introduced in [32] to capture the dynamic connection between the penalty signal and a penalty-aware demand that reacts to it. Typically, energy flexibility is characterised using static functions for specific stable states that do not account for changes over time, so the FF aims to explain the dynamic behaviours that result from utilising energy flexibility. It is crucial to observe the dynamics because activating energy flexibility inherently involves deviating from normal operational set points. The FF can be developed by analysing time-series data, simulations, or from the first principles of a comprehensive model that encompasses constraints, occupancy behaviour, controllers, and boundary conditions. An illustration of an FF is provided in Figure 2.2, where energy flexibility can be characterised by the following parameters [30]:

- τ, the time delay from when the penalty signal is adjusted to the earliest response in demand. This delay can be caused by communication delays or, in some instances, by extensive computation in optimisation algorithms. Additionally, certain appliances may require time to complete their current operations before they can be shut off.
- α, the duration for flexibility to become fully activated after the beginning of the response. This is influenced by the reaction speed or the energy inertia of the flexibility source.
- β, the duration for which the flexibility can be activated, which varies based on the energy capacity of the flexibility source. For instance, well-insulated, large, heavy buildings can have long durations, whereas smaller, poorly insulated buildings cannot adjust their demand for significant periods.
- Δ, maximum demand adjustment that refers to the power capacity of the flexibility source.
- A, the total amount of energy that the flexibility source can decrease (or increase) in demand before reaching the constraints set by the owner of the flexibility source. It is a crucial factor if activating flexibility requires shifting significant energy.
- B, represents the total energy required to rebound from the deviation caused by the previously activated flexibility. The type of flexibility source influences this. For instance, if heating is turned off to reduce demand, it will subsequently need to be turned on again to return to the initial temperature. However, in the case of dimmed lighting, there is no need to increase the brightness above normal levels afterwards; therefore, in such case, there is no rebound.

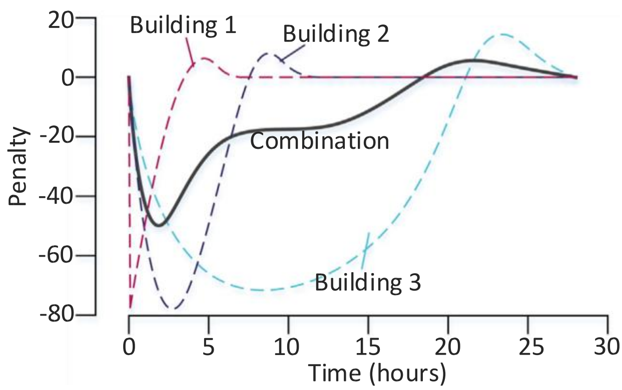

Figure 2.3. Flexibility functions of buildings with different energy inertia.

FF can be used to assess an individual or a group of flexibility sources, such as a single building or a combination of buildings. Figure 2.3 illustrates an instance of FF for buildings with varying thermal mass. Building 1 possesses a substantial thermal mass, resulting in a notable rebound effect, building 2 is of medium size, and building 3 has poor insulation and resistive heating. The combined FF of these buildings is depicted by the black line.

2.2 Sources of energy flexibility

Buildings have great potential to be used as a source of aggregated energy flexibility. In 2018, the building sector in the EU was responsible for about 40.3% of final energy usage (26.1% in households and 14.2% in the service sector) [33]. Various factors influence the energy flexibility that a building can offer [32]:

- The physical attributes of a building (including its thermal mass, insulation, and architectural layout).
- The controllable loads within the building (such as ventilation, heating, and storage equipment).
- The installed control systems that allow controllable loads to respond to external signals (such as control or penalty signals based on electricity price, emissions, etc. [34]).
- The behaviour of the building occupants and their comfort needs.

The Annex 67 project categorised building energy loads into three groups according to their importance and the necessary conditions for adjusting or altering their consumption.

- **Shiftable loads** can be rescheduled to off-peak hours by using a penalty signal. These loads can usually be rescheduled without significantly affecting the occupant's comfort. Shiftable loads are further categorised into **shiftable profile loads**, such as washing machines, which have a fixed energy profile but can be moved, and **shiftable volume loads**, such as charging devices, which allow the energy profile to change within certain limits while meeting the total volume over a specific time period [35].
- **Non-shiftable loads,** such as lighting, cooking appliances, computers, and televisions, cannot be easily adjusted and cannot be moved, regardless of the energy cost. This is primarily because of occupant comfort requirements.
- **Other controllable loads** can be regulated using optimal control methods through thermostat adjustments, fan speed regulation, or dimming (for example, in HVAC systems, water heaters, and non-essential lighting).

2.2.1 Residential flexible loads

The flexibility of residential loads can be defined based on the type of appliance they are, categorised as storable, non-storable, shiftable, non-shiftable, curtailable, or non-curtailable loads [36], [37]. This categorisation helps to deduce an appliance's potential to participate in demand response. Residential loads can be first grouped into storable and non-storable loads, with non-storable loads further classified as shiftable and non-shiftable. Additionally, non-shiftable loads can be subcategorised into curtailable and non-curtailable loads. Non-curtailable loads, such as non-storable, non-shiftable, and non-curtailable, are considered inflexible base loads that cannot be controlled.

- **Storable loads** decouple power consumption from the end-use service through the use of batteries or thermal inertia. These types of loads store electrical energy in a different form, such as thermal or electrochemical. Examples of this type of load include batteries, electrical heating/cooling (HVAC) [38], and domestic electric water heating (EWH) appliances that store energy in a thermal mass.
- **Shiftable loads** can be rescheduled in time to operate earlier or later than they should because they have temporal flexibility. It is necessary to plan ahead for shiftable loads, as they often have a predetermined operational

cycle that must be maintained. Some examples of shiftable loads include washing machines, dryers, and dishwashers.

- **Curtailable loads** cannot be shifted because of the consumers' comfort requirements or because there is no need to shift them, such as in the case of room lighting. Nevertheless, curtailable loads can be stopped if consumers are provided with enough incentives.

A summary of typical residential loads based on the aforementioned classification and their adaptability features is provided in Table 2.1. In order to evaluate the potential for aggregation of flexible loads, it is possible to categorise them based on whether they are capacity or energy-based, their response direction (unidirectional upward or downward, or bidirectional), speed of response, duration of response, availability, and predictability [39].

- The **type (capacity or energy)** indicates the energy-to-power ratio of the flexible load. Flexible loads with a low ratio can deliver high power but cannot sustain it for a long time, making them more suitable for providing short-term flexibility services such as ancillary services. On the other hand, loads with a high ratio can provide power for extended periods and are therefore categorised as energy-type loads, making them better suited for longer applications like load levelling.
- The **response direction** determines the direction of power flow for the load. Some may only be in one direction, either up or down, and function as either a load or a producer, but not both. Bi-directional sources of flexibility, such as battery storage devices, can operate as prosumers, sometimes consuming power and other times supplying power.
- The **response speed** at which residential flexible resources activate is typically fast, ranging from seconds to minutes, but it also relies on the availability of the load for flexibility usage.
- The **response duration** is the time period for which a flexible load can maintain its power at the maximum level in relation to its nominal power when required. According to [39], the maximum response duration can sometimes be calculated by dividing the allowable energy range by the maximum power capacity (for example, for a 50 kWh battery with a 10 kW charging/discharging power, it would be 5 hours). The response duration of flexible loads may vary based on the technology used and consumer behaviour.
- The **availability** determines how often and when the flexible load is available for activation, which varies depending on the load. Electric vehicles, for example, are typically accessible in the evening and at night, as they are often parked away from residential areas during the day. Conversely, wet appliances may have limited availability, as they can only be activated at specific times and usually once a day.
- The concept of **predictability** refers to the accuracy of estimating the availability of a flexible load. Certain loads, such as battery systems, can be highly predictable, while electric vehicles (EVs) are more likely to be accessible between 6 PM and 6 AM. On the other hand, loads like washing machines and dishwashers are less predictable due to their usage being limited to a few hours per week and being influenced by consumer behaviour.

Table 2.1. Characterisation of residential flexible loads.

Appliance type	Storable appliances					Non-storable appliances		
						Shiftable appliances	Non-shiftable appliances	
							Curtailable	Non-curtailable
Flexibility characteristics	**Electric Vehicles (EV)**	**Battery Storage (BESS)**	**Heating and cooling (HVAC)**	**Electric Water Heater (EWH)**	**Refrigerators**	**Wet appliances and dryers**	**Lighting**	**Cooking Devices and other 'must-use' home devices**
Interruptible	Yes	Yes	Yes	Yes	Yes	No[1]	Yes	No
Capacity or energy type	Both	Both	Capacity	Both	Capacity	Capacity	Depends[2]	-
Response direction	Bidirectional[3]	Bidirectional	Downward	Downward	Downward	Downward	Downward	-
Response speed	Quick	Quick	Fast	Fast	Fast	Moderate	Quick	-
Response duration	Hours	Hours	Minutes	Hours	Minutes	Minutes	Hours	-
Availability	Evening and night	Always	Often	Often	Always	Rarely	Evening	-
Predictability	High	Perfect	High	High	High	Moderate	Good	-

[1] Wet appliances such as washing machines are interruptible for up to couple of minutes.
[2] New efficient low-power LED lighting systems are energy type while older less-efficient lighting systems are power type.
[3] With vehicle-to-grid technology EVs can respond in both directions.

2.2.2 Distributed battery storages

Compared to flexible loads that only consume energy, battery storages operate bidirectionally as prosumer devices, offering energy flexibility by adjusting their demand profiles. Battery storage systems are valuable for energy flexibility because they can store electrical energy for future use.

Battery storage systems are frequently installed alongside PV systems to allow for the self-consumption of PV power on-site [40]. Storing surplus PV energy for later use can lessen the strain on distribution grids during peak demand periods [41] and alleviate PV curtailment during low-demand midday hours when PVs often generate excess power [42].

Distributed battery storages are a crucial source of energy flexibility for aggregators due to their rapid response time, immediate availability, constant knowledge of state-of-charge (SOC), and direct electrical energy flexibility. In contrast, flexible loads achieve energy flexibility indirectly through control of temperature or scheduling of loads [43].

Aggregated battery storages can serve other purposes that individual residential owners of smaller storage systems cannot achieve:

- When the aggregated battery storage reaches a sufficient capacity, the aggregator can utilise it to take part in the reserve markets [44]. Battery storage is well-suited for this purpose because of its quick response time.
- Aggregators can manage the energy distribution of battery systems within a community through energy sharing to enhance the self-consumption of renewable energy [45]. They can also be used for local power balancing [46] and peak shaving [47], which helps decrease the ramping stress on traditional power generation during periods of rapid changes in demand.
- Aggregated battery storage can offer extra support for ancillary services [48], such as congestion management [49] on the distribution grid and black start support [50].

2.2.3 Electric vehicles

Considerable research has been devoted to exploring the use of electric vehicles (EVs) as sources of flexibility, given the increasing adoption of EVs. When compared to stationary battery systems, EVs present more complex factors to consider. Their inherent mobility can be viewed as either an advantageous feature or a disadvantage in certain situations.

The mobility aspect of electric vehicles allows them to travel between different parts of the grid. For residential energy flexibility aggregators, this means that the vehicles may not always be available as their owners use them to commute to various locations. Therefore, research on residential EV energy flexibility has significantly been focused on overnight charging [51]. The development of non-residential charging infrastructure will be crucial for utilising daytime charging as a source of flexibility.

Most EVs are parked and not in use for approximately 22 hours a day [52], which means they could be utilised for other purposes during that time, such as providing demand response, ancillary services, utilising renewable energy generation on-site, and peak shaving. However, an intermediate aggregator is needed to engage EVs in these applications.

The primary focus of research on EV flexibility has been on determining the best scheduling and optimisation strategies for charging to minimise costs [53], [54]. This is often studied in the presence of renewable generation.

Unidirectional charging isn't the only function of EVs. When paired with smart charging infrastructure, EVs can also offer vehicle-to-grid (V2G) capability, making them bidirectional devices. With V2G technology, EVs can charge and discharge, essentially serving as mobile battery systems. However, V2G must be approached with caution due to battery degradation considerations. Offering frequency containment reserve (primary reserve) can contribute an additional 1–2% degradation to the typical 7–12% capacity reduction over 5 years [55]. As per [56], providing a combination of frequency containment reserve and peak-shaving is more profitable than offering either of them individually.

The use of residential electric vehicles for frequency regulation was examined in [57] by analysing the dynamic relationship between the battery SOC and the frequency target in the system. In a similar study [58], it was found that the ability to regulate power bidirectionally during the daytime was approximately one-third less than that during the nighttime because there were fewer parked cars in the residential grid.

An analysis of the EV charging infrastructures, the main roles and participants of markets, and the future governmental interventions required for extensive EV advancement is provided in [59].

2.3 Demand-side flexibility aggregation

Due to the untapped potential for energy flexibility, a new market participant known as the aggregator has appeared. The aggregators' role involves pooling together a variety of smaller flexibility resources to function as a larger entity, as an individual residential or commercial customer often lacks sufficient capacity to engage in the markets independently. Therefore, the aggregator plays a crucial role in transforming passive residential or commercial consumers into prosumers by consolidating the energy flexibility of their adjustable loads. The aggregator has the potential to deliver significant benefits to power systems. As noted in [60], the aggregator can offer fundamental, transitory, and opportunistic value. The fundamental value arises from the process of aggregation itself, while transitory value refers to the temporary worth generated as the power system progresses from older regulations and technologies to newer, more advanced ones. Opportunistic value, on the other hand, emerges in response to regulatory flaws.

2.3.1 Existing energy flexibility markets

At present, aggregators can trade flexibility in markets that have traditionally been structured for centralised power plants. As a result, an individual residential household cannot independently engage in these markets. Consequently, aggregators can potentially combine the flexibility of numerous smaller producers and sell it in the markets. The markets where flexibility can be traded currently include markets such as the day-ahead, intra-day, and balancing reserve markets. The first two are organised by power exchanges, such as Nord Pool or EEX, while the third is managed by regional TSOs. A comprehensive overview of the involvement of aggregators in these markets is provided in [61].

The **day-ahead market** (DAM) facilitates bidding for the purchase or sale of energy production for the following day by the hour. Bidding typically closes at noon the day prior to delivery. This means that for participation in the DAM, aggregators must forecast the available flexibility at least one day in advance while accounting for reasonable uncertainties. A significant amount of research has been conducted on how aggregated flexibility can be utilised in DAMs [62]. Many studies in this area focus on maximising profits under various conditions utilising different approaches. For instance, a robust optimisation model for an EV profit-maximising aggregator is introduced in [63], which demonstrates that their model can reduce deviations from energy balance by approximately 9–15% compared to stochastic models and 60–64% compared to deterministic models. Additionally, a stochastic optimisation model was created in [64] to establish an optimal day-ahead bidding strategy to increase an EV aggregator's profits. A coordination optimisation model based on marginal pricing was created in [65] using mixed-integer linear optimisation to manage two EV aggregators. A forecasting model utilising support vector machines was developed for aggregated smart household flexibility in the context of the day-ahead market [66], which was further advanced in [67] by establishing an optimal bidding strategy for load aggregators to mitigate financial risks associated with price fluctuations. A robust optimisation model aimed at minimising the operational costs of smart household aggregators was developed in [68], resulting in a 5.7% cost reduction. An optimal bidding strategy for a multi-energy virtual power plant aggregator was devised in [69], achieving approximately a 5% cost decrease. An optimal bidding strategy for a multi-energy distributed energy resources (DER) aggregator was formulated in [70] using stochastic mixed-integer linear programming for the day-ahead market.

Bidding in the **intra-day market** (IDM) occurs on the delivery day. Participation in IDM can utilise more precise forecast data acquired closer to the delivery time. Therefore, for aggregators, engaging in an intra-day market may serve as a strategy to mitigate the risks associated with inaccurate day-ahead flexibility forecasts [71]. A model for an incentive-based demand response program was developed in [72] for involvement in both the day-ahead and intra-day markets. The research findings indicate that participating in the intra-day market can be financially comparable to participating in the day-ahead market. It was noted that there is a scarcity of research concerning aggregated flexibility provision in intra-day markets.

The **balancing market** aims to address frequency deviations caused by imbalance issues or unexpected generation loss by acquiring reserve capacity [73]. The EU Commission has set a regulatory guideline for energy balancing to standardise balancing markets across Europe [74]. This regulation requires all EU member states to eventually offer three types of balancing reserve products: automatic Frequency Restoration Reserve (aFRR), manual Frequency Restoration Reserve (mFRR) – which represents secondary and tertiary reserves – and Replacement Reserve (RR). Additionally, the Frequency Containment Reserve (FCR), known as the primary reserve, is being adopted voluntarily throughout Europe.

The bidding process for RR concludes 1 hour before the delivery time and 30 minutes before the delivery for aFRR and mFRR [75]. Thus, although tapping into the reserve markets may seem appealing to aggregators due to the minimal forecast errors associated with near real-time operations, participation in these markets necessitates flexible power that can be deployed rapidly. The maximum activation time required is 5 minutes for aFRR, 12.5 minutes for mFRR, and 30 minutes for RR [75]. The potential of aggregated energy flexibility from EVs in reserve markets has been explored in [76], [77], [78], [79], [80], [81]. Similarly to DAM publications, generally, the emphasis is on maximising profits through optimal bidding strategies utilising various optimisation techniques.

2.3.2 Emerging markets for flexibility

2.3.2.1 Local flexibility markets

Local flexibility markets (LFMs) are platforms for trading electricity where flexibility can be traded in specific geographical areas, like small towns, neighbourhoods, or communities [82]. The models and clearing methods for local flexibility markets are reviewed in [27], revealing that participants in LFMs may hold overlapping roles; either the DSO or aggregator can operate the LFM, or the aggregator might also serve as its own balance responsible party (BRP). As a result, LFMs can be tailored to accommodate various conditions and regulatory frameworks. Additionally, the interaction between LFMs and the balancing market must be taken into account if the TSO acquires flexibility from the LFM through coordination with the DSO. The significance of TSO-DSO coordination is further emphasised in [83] and [28].

One of the initial large-scale demand response demonstrations occurred within the EcoGrid EU project [84], involving approximately 1,900 residential customers, where real-time pricing was utilised to encourage changes in consumption. It was found that price incentives provide the DSO with limited security since they merely encourage loads to adjust their consumption rather than mandating it. Furthermore, pricing structures penalise rigid loads that cannot shift or alter their consumption.

These limitations were tackled through the EcoGrid 2.0 project [85], which involved aggregating flexible loads and trading them on a fully operational experimental LFM under realistic conditions. In that initiative, two categories of services were established to manage congestion in the distribution grid: capacity limitation services and baseline flexibility services. It was demonstrated that these services can offer an additional safety net against network overloads and outages; however, their necessity is infrequent. Additionally, it was also pointed out that there are widespread shortcomings and unrealistic assumptions in the literature. Clear definitions for flexibility services are rarely provided, indicating that there are currently no well-defined standardised flexibility products available. A similar concern was highlighted in the quantification section of this thesis, where an excessive number of quantification parameters were observed, underscoring the need for standardised flexibility products that would outline the outcome parameters for quantifying flexibility to enable its sale as realistic products.

In [86], a decentralised LFM design that was introduced that accounts for demand uncertainty alongside a right-to-use (RtU) option, enabling the DSO to reserve flexibility that can be activated in real-time to address potential congestion with medium likelihood. A study in [87] explored an LFM design that enables the provision of various flexibility services at the distribution network level. In this proposed framework, the aggregator facilitates flexibility trading within the local energy community, functioning as a local market operator. An assessment of twenty-three distinct European LFM design proposals for congestion management was conducted in [88]. The findings revealed that the majority of these market design proposals do not fulfil the criteria of a "market"; furthermore, the definitions of products, contract lengths, market clearing processes, and matching methods showed significant variation across different designs.

2.3.2.2 Peer-to-peer trading

A novel concept of peer-to-peer (P2P) trading has emerged recently [89]. The concept of P2P trading enables peers (prosumers and consumers) to exchange energy directly. This promotes the local use of surplus renewable energy generated within the community. P2P trading can serve as a means to engage end-users in energy transactions, as opposed to traditional capacity and balancing markets, which impose minimum capacity requirements. However, there is no agreement on the optimal market design, such as trading methods, clearing processes, regulatory mechanisms, or business models that P2P trading should adopt.

Research has identified essential components and strategies in P2P energy trading by creating a three-dimensional system framework [90]. The first dimension focuses on enabling the seamless exchange of information among the power grid layer, ICT layer, control layer, and business layer. The second dimension takes into account the size of the participants, which includes premises, microgrids, cells, and regions. In the third dimension, the temporal aspect of P2P trading is represented through the processes of bidding, exchanging energy, and settling transactions.

There have been several real-life demonstration projects related to P2P trading [91], including EnerChain, Electron [92], Piclo [93], SonnenCommunity [94], and Vandebron [95]. An overview of these and additional P2P initiatives can be found in [96], [97], and [98]. A trading platform named "Elecbay" was developed in [90] to support P2P trading within a grid-connected LV microgrid. That study indicated that a greater variety of energy consumers and prosumers can enhance the balance of local generation and consumption.

In [99], three types of P2P market designs were suggested: bill sharing, mid-market rate, and auction-based pricing methods. It was determined that with moderate PV penetration, P2P trading could lead to a cost reduction of approximately 30% for end-users. According to another study [100], P2P trading achieved savings of 16%, and when combined with either centralised or decentralised battery storage, it resulted in savings of 24% and 31%, respectively.

The study in [98] examined three distinct designs for P2P markets: a complete P2P market design in which peers engage in direct trade with one another; a community-based market design that involves a community manager facilitating inter-community trading and acting as an intermediary between the community and the broader system; and a hybrid P2P design that merges the two previous approaches, establishing a hierarchy of various layers where peers trade directly within their own layer. The paper concluded that the hybrid P2P market design serves as an effective compromise, offering appropriate scalability while allowing for P2P interactions.

A hierarchical framework is proposed in [101] that facilitates peer-to-peer (P2P) trading through smart contracts based on blockchain technology across residential, commercial, and industrial domains. It is observed that scalability presents a challenge for the execution of P2P trading. To tackle the scalability issue, the authors of [102] suggested a dynamic allocation of P2P clusters that optimally aligns various load and renewable profiles that can enhance each other. The advantage of clustering is highlighted as the improved scalability of P2P trading with an increasing number of participants.

A thorough review of P2P energy trading is presented in [103], highlighting key research areas as follows: (1) the architecture of trading platforms, security assessments, and scalability; (2) transaction mechanisms that utilise blockchain technology; (3) modelling participant behaviour through game theory; (4) simulations to validate the other primary subjects; (5) strategies to enhance the economic advantages for peers; and finally, (6) algorithms that integrate the aforementioned primary topics.

2.3.2.3 Selling energy efficiency

An alternative business model for aggregators could involve selling surplus energy efficiency (EE) to entities that are unable to meet the legally mandated EE requirements [104]. This is necessitated by the various emissions, environmental, and energy efficiency regulations that generation stakeholders must follow. If the energy efficiency achieved through the aggregated flexibility exceeds the legally required minimum, the business model would need to monetise this surplus EE for profit. This type of demand response (DR) business approach is commonly known as "energy savings certificates (ESC)", "energy efficiency credits (EEC)", or "white tags" [105].

2.4 Barriers and challenges faced by aggregators

The EU has recognised through the Internal Electricity Market Directive [106] that in the future, "market participants engaged in aggregation are likely to play an important role as intermediaries between customer groups and the market". Consequently, they have established various regulatory guidelines [74], [106], [107] to motivate Member States to eliminate discriminatory provisions and obstacles concerning aggregators' access to electricity markets and their involvement in ancillary services. Nonetheless, it is the responsibility of each individual Member State to "choose the appropriate implementation model and approach to governance for independent aggregation while respecting the general principles set out in this Directive" [106].

The Clean Energy for All Europeans Package [107], issued in 2019, established new regulations aimed at creating a more flexible and market-driven EU electricity market that can accommodate a more significant proportion of renewable energy sources. While it does not mandate that Member States actively support aggregation business models, the package instead focuses on ensuring fair market conditions for aggregators, with the expectation that once a "levelled playing field" is established, innovative products and services will emerge [108].

The survey [109] carried out by the European Network of Transmission System Operators for Electricity (ENTSO-E) regarding the procurement of ancillary services and the design of electricity balancing markets reveals significant variances in market designs across European countries. These disparities could be attributed to the historical development of markets in these countries or arise from the mix of electricity generation; some countries rely on fewer large, traditionally centralised producers, while others utilise a more significant share of renewable energy in a decentralised approach.

Due to varying market designs, the obstacles for aggregators to enter the markets differ by country. The challenges for aggregators in Denmark, France, Germany, and the UK were evaluated in [110]. Similarly, the hurdles in Austria, Germany, and the Netherlands were examined in [111], and the authors of [112] investigated the Belgian, Finnish, French, and UK market barriers. Barriers preventing participation in ancillary services within the U.S. electricity markets were also analysed in [113]. The general obstacles that deter customers from participating in demand response programs are discussed in [114].

A modular framework was created in [142] to evaluate the obstacles faced by distributed energy resources (DERs) in primary and secondary reserve markets. This framework is organised into three hierarchical modules, with the first having a more significant influence than the second, which in turn influences the third the most. The first module addresses "rules regarding the aggregation of DERs", which include technical biases against combined resources, interoperability between DSOs, and levels of aggregation. The second module covers barriers from "rules defining the products in the market", such as minimum bidding requirements, product time definitions, proximity to real-time reservations, and product symmetry. The challenges in the third module arise from "rules defining the payment scheme for grid services", which involve the payment type and additional incentives for flexibility.

The research discussed in [110] was further developed by the authors of [111] and [112] who introduced their models to categorise the obstacles faced by DER aggregators. According to the framework established in [111], barriers that prevent aggregators from participating in the electricity market can primarily be divided into two categories: those related to market access and those related to auction configuration. Market access barriers encompass formal access requirements, administrative elements, and technical prequalification criteria, whereas auction configuration barriers consist of bid-related specifications, time-related factors, and remuneration issues. The framework presented in [112] classifies barriers into three types: regulatory, technical, and economic.

According to [110], to encourage aggregator participation, the rule changes should involve lowering the minimum bid size, adopting a more adaptable definition of the delivery period, conducting auctions daily, and allowing the delivery of asymmetrical products. Research of [111] indicates that flexible pooling conditions, increased bidding frequency, improved product resolution, and the acceptance of non-precontracted bids could facilitate the integration of DERs into the market. Additionally, the authors of [112] suggest that the minimum bid size, bid symmetry, and product resolution significantly influence aggregator income.

Building on previous researchers' work, the barriers aggregators face are categorised in this thesis into four categories: those related to the regulatory framework, market conditions, economic challenges, and the technological aspects of aggregation. A summary of these barriers is provided in Figure 2.4.

The **regulatory framework barriers** include restrictive rules prohibiting or hindering aggregators' operations. The organisations that create these regulations may consist of government bodies, regulatory agencies, TSOs, and other entities with authoritative power. Examples illustrating the origins of regulatory framework barriers may include:

- **Explicit discrimination against aggregated resources**: Some rules may explicitly favour certain players, like large industrial participants, disadvantaging aggregated resources. TSOs and DSOs might also prefer players connected to their specific grid region; however, aggregated resources can include units from various parts of the grid.
- **Inadequate definition of clear roles and responsibilities for market actors**: The insufficient clarity in defining the roles and responsibilities of market participants is a significant obstacle across Europe, as it restricts free-market competition, raises risks for all involved, and can lead to the violation of consumer rights [115].
- **Prequalification requirements**: Balancing service providers must meet specific prequalification criteria to confirm that their systems can technically supply the necessary products. Guidelines should be established to facilitate the aggregation of DERs; otherwise, aggregators will have to prequalify every unit in their portfolio, undermining the purpose of aggregation, which relies on the combined strength of smaller resources.
- **Portfolio requirements**: Rules might be implemented to regulate the unit mix of aggregators' portfolios. For instance, there could be requirements regarding

the proportion of relatively uncertain sources such as VREs and flexible loads compared to more reliable sources like battery storage and traditional generation or demand.

- **Additional agreements**: Aggregators might need to secure authorisation from other market players. For example, the consent of a large consumer's energy supplier or the BRP might be necessary [111].

Market aspect barriers are challenges that arise from the market side when an aggregator aims to offer flexible resources.

- **Lack of specific products for flexibility service**: The guidelines for LFMs remain undefined, which currently prevents aggregators from tapping into this revenue source.
- **Incompatible product definitions of traditional services**: Traditional balancing product specifications were designed with conventional generation in mind. Certain specifications significantly hinder the development of flexibility aggregators; for example, the minimum bid size in many market structures is too large for smaller aggregators to meet. The requirement for bid symmetry limits the usable flexibility resources, as flexible load-oriented demand response aggregators typically have greater potential for downward regulation. Other factors that may influence the ability of aggregators to offer flexible resources include timing considerations, such as notification period, delivery time, and delivery length.
- **Market bidding and clearing frequency**: In balancing markets, the frequency of bidding and clearing directly impacts how long flexible resources must be reserved if they need to be activated. If this frequency is low, it complicates aggregators' ability to accurately predict their available resources in advance, which diminishes their confidence in participating in these balancing markets [115].

Economic barriers refer to obstacles that affect the profitability of aggregation. Some of these include:

- **Initial investment costs**: In contrast to traditional plants, where expenses are clearly defined, the costs associated with aggregation are not as easily understood. Residential flexibility aggregators face technical expenses related to the installation of smart meters and communication and control technologies, which can lead to significant initial investment costs. The minimum bid size of 10 MW or greater adds to this concern, as aggregators must engage a substantial number of residential customers in their portfolio before they can participate in the market and have a chance for financial returns.
- **Inadequate subsidisation**: Peaking power plants compete directly with aggregated services. Providing subsidies to these plants can create an uneven playing field since they are already well-established. Instead, the encouragement of largely untapped energy flexibility resources offered by aggregators should receive subsidies.
- **High penalisation**: Maintaining a balance between production and consumption is crucial for system reliability, so there should be penalties for non-delivery. However, these penalties should not be excessively high to exclude aggregated resources from markets.

Technological implementation barriers refer to the challenges aggregators face when carrying out aggregation.

- **Lacking ICT infrastructure**: The successful technological implementation of aggregation depends on having sufficient ICT infrastructure. These barriers can be broadly categorised into sensing-related, computing-related, and communication-related issues [116]. Comprehensive metering and data collection are vital for assessing the availability and predicting flexible resources. Therefore, a high penetration rate of smart meters is critical for successful aggregation. Managing substantial data volumes also incurs high computational costs, necessitating powerful servers. Additionally, the communication aspect must prioritise ensuring data security and privacy.
- **Lack of widespread "Smart Grid Ready" devices**: Home appliances must be controllable via a data connection for the aggregation of residential energy flexibility. Although the number of smart devices is on the rise, a significant obstacle is the lack of standardised software needed to connect and manage SG-ready devices.
- **Interoperability among DSOs**: The technological implementation is also complex from the grid perspective, as the aggregator's portfolio may include units from different regions managed by different DSOs. This is particularly important for electric vehicles (EVs) that may transition from one DSO's region to another within the same day [110].

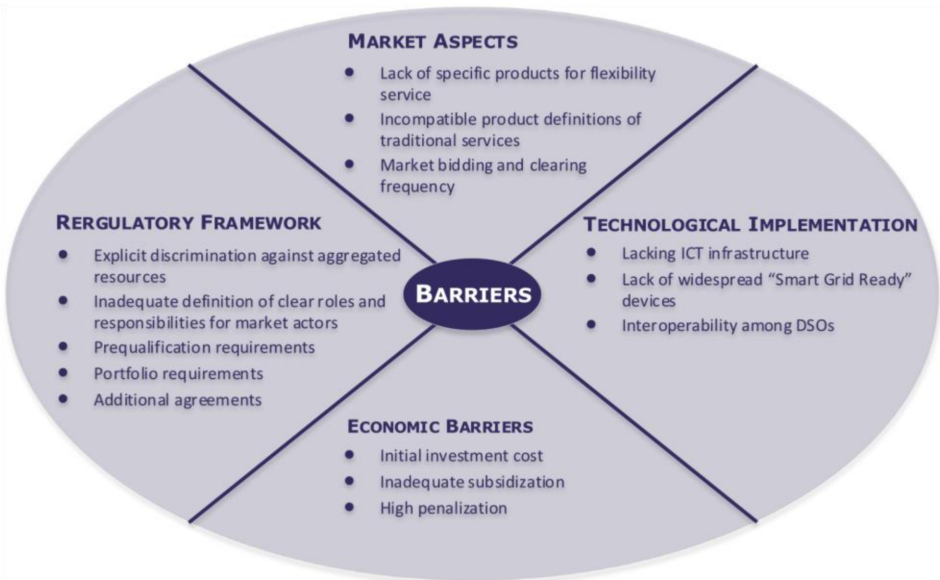

Figure 2.4. Summary of barriers faced by aggregators.

2.5 Conclusions

The state-of-the-art review highlights the growing importance of energy flexibility as a cornerstone of modern energy systems, driven by the increasing penetration of variable renewable energy sources and the need for improved grid stability. This chapter explored the critical dimensions of energy flexibility, including its definitions, sources, aggregation, and challenges, while emphasising its role in transitioning toward sustainable and efficient energy systems.

The analysis of existing sources of energy flexibility has shown that residential flexible loads, distributed battery storage systems, and electric vehicles offer unique opportunities and challenges. Although flexible loads and batteries can deliver significant flexibility, their activation is limited by physical and operational constraints. Electric vehicles add further complexity because of their mobility and unpredictable availability. Aggregating these resources is essential to facilitating substantial engagement in energy markets; however, obstacles like communication infrastructure, market design, and regulatory issues continue to exist.

While the potential benefits of energy flexibility are clear, this review also acknowledges the barriers and challenges aggregators face. These include the technical complexities of integrating diverse flexible loads, regulatory constraints, and market dynamics. Emerging markets for energy flexibility offer promising opportunities, yet they require robust frameworks and technological advancements to fully realise their potential.

In conclusion, this chapter's review establishes a foundation for analysing existing quantification methods and identifying their shortcomings, which will be discussed in the next chapter.

3 Analysis of demand-side energy flexibility quantification methods

To successfully incorporate demand-side flexibility into energy systems, suitable quantification methods are necessary. This chapter provides an analysis of current approaches for quantification, emphasising their advantages and drawbacks. The discussion delves into how various quantification frameworks – spanning from single-value metrics to more intricate models – represent the dynamic characteristics of flexibility. Special emphasis is placed on the impact of asymmetry and non-linearity in existing methodologies, setting the development of a more robust quantification method in the following chapter.

3.1 Existing quantification methods

A brief summary of methods and frameworks for quantifying energy flexibility is provided in Table 3.1. The evaluation encompasses the parameters, metrics, and indices used in flexibility quantification. Flexibility quantification methods can generally be classified based on whether they assess flexibility as a single value or as a curve or region that illustrates the relationship between two or more variables, as well as whether symmetry or linearity is taken into account. It was observed that when flexibility is assessed using a singular value, it is usually measured in relation to flexible power or energy values [25], [117], or temporal factors such as the duration that consumption can be altered [118], or in a more conceptual way through flexibility indices that, for instance, indicate flexibility's capability for load covering, shifting, and scheduling [24]. Conversely, when a curve is employed, it establishes a correlation between two parameters, such as flexible energy and activation cost [23]. More sophisticated methods define flexibility as a region or domain of workable operations considering factors like network constraints, ramp rates, and others [119].

Another key element is whether the method of quantification recognises flexibility as a non-linear and asymmetrical resource. The concept of "asymmetry" refers to the disparity in the capacity to increase or decrease demand. In this context, the coincidence factor plays a crucial role for loads. For example, electric water heaters exhibit a low coincidence factor, indicating that only a small portion is in use at any one time. Therefore, there are many more water heaters that could be activated to boost demand, unlike the limited number of devices available to lower demand. The same principle applies to battery systems, which are not consistently at a 50% state-of-charge to provide equal up- and downregulation capabilities. Thus, when assessing the flexibility of an entire portfolio, it becomes evident that there are unequal levels of flexibility available to increase or decrease demand. It is vital for quantification methods to consider the asymmetry of flexibility, as some markets necessitate symmetrical bids, even though the sources of flexibility are often not symmetrical.

Linearity refers to the existence of a linear connection between two or more variables; for instance, the relationship between power and the duration for which flexibility can be enabled. A consideration of the non-linear nature of flexibility is crucial for providing an accurate estimate of flexibility, as there may be a non-linear correlation between power and duration, power and cost factors, etc. The flexibility envelope approach outlined in [120] considers the asymmetry by offering envelopes for both upward and downward regulation. The cost curves method discussed in [23] takes into account both asymmetry and non-linearity by depicting flexibility as the connection between available flexible energy and the associated costs, represented as a curve for both demand increases and decreases. According to the literature review, there is a shortage of quantification methods that address both the asymmetry and non-linearity of energy flexibility. Hence, this thesis proposes a novel quantification method that assesses the relationship between flexible power and energy with respect to the duration of its activation while factoring in the asymmetrical nature of non-linearity.

Table 3.1. Overview of quantification methods for energy flexibility.

Ref.	Short description	Case study	Quantification parameters, metrics, indices	Flexibility quantified using a single value, curve, or a region	Considers asymmetry, non-linearity
[25]	A unified framework is proposed for capturing the DR potential of thermal and electrical systems	One building with heat pump, PV system, EV, and BESS	Indices of self-consumption, storage capacity, storage efficiency	Single value	Asymmetry
[24]	A quantification methodology for five energy flexibility indices is proposed	Office building with HVAC, dimmable lighting, EV charging	Indices related to load covering, shifting, scheduling, moderate regulation, and fast regulation	Single value	No
[121]	A methodology that models flexible resources as a virtual energy storage system	Office and apartment building ventilation systems	Power and energy capacity, State of Charge, self-discharge rate	Single value	No
[117]	The proposed model schedules a set of appliances and calculates the aggregated flexibility according to the energy and flexibility prices	Aggregated HVACs, pool pumps, electric water heaters	Flexible power	Single value	No
[23]	A methodology for computing the flexibility of buildings using cost curves	Office building HVAC	Flexible energy and its related cost	Curve	Asymmetry and non-linearity
[119]	A framework to model and characterise DER flexibility using the concept of nodal operating envelope under network constraints, ramping rate, cost, etc.	Distributed network consisting of a BESS, load, and a generator	PQ chart of a flexible operating region	Region	Asymmetry and non-linearity
[120]	A methodology based on determining the flexibility envelopes of two boundaries conditions when loads are activated either as early or as late in the day as possible	Wet appliances, domestic hot water buffers and EVs	Flexible power and energy	Region	Asymmetry
This thesis	The proposed method quantifies energy flexibility as a power-duration curve	Aggregated residential heat pumps	Flexible power and energy, duration of activation	Curve	Asymmetry and non-linearity

3.1.1 Flexibility envelope

The flexibility envelope concept is proposed in [122] to quantify energy flexibility. This method involves determining the two extreme scenarios of operation when demand is shifted to either as early as possible or as late as possible. The methodology for quantifying flexibility is depicted in Figure 3.1, where flexibility is employed to (a) increase or (b) decrease power consumption.

The lines $E_{\max}$ and $E_{\min}$ represent upper and lower energy boundaries that illustrate the two extreme scenarios. The upper energy boundary is determined when all flexible devices are set to consume as early and as much as possible. This results in high power consumption until user comfort and system constraints are reached, such as when the room temperature hits a specified upper limit, and the heating is turned off, or schedulable appliances like washing machines complete their cycle and do not need to be turned on again for a while. Similarly, the lower energy boundary is achieved when all devices are programmed to consume as late and as little as possible. In this case, the operation of devices is delayed until lower constraints are reached, for example, when the domestic water heater becomes too cold, or the latest deadline for the dishwasher to turn on is reached.

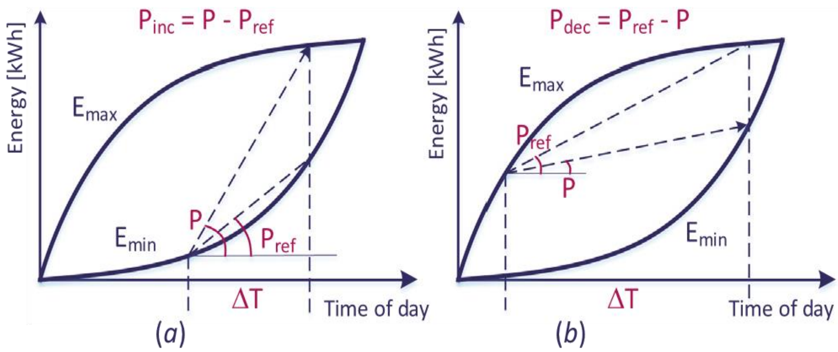

Figure 3.1. Concept of the envelope quantification method: (a) flexible increase and (b) flexible decrease in power consumption.

The limitations of this approach include its assumption that the system's starting and ending conditions are predefined. Additionally, it has been noted in [122] that this quantitative method primarily indicates potential flexibility rather than serving as a tool for scheduling or calculating the rebound effect.

The quantification method was employed in [123] to quantify a home's flexibility using a rule-based controller and model predictive controller with cost-oriented, emissions-oriented, and flexibility-oriented objectives.

The flexibility envelopes were developed further in [124] to encompass non-intrusive load monitoring (NILM) for disaggregation of shiftable appliances from overall energy consumption. The study findings showed that the NILM integrated quantification method accurately identified 90% of the available energy flexibility. The overall characterisation of energy flexibility was enhanced by 40%.

3.1.1 Nodal operating envelope

A framework is introduced in [125] to model, describe, characterise, and quantify the flexibility of distributed energy resources (DER) based on a nodal operating envelope (NOE). The NOE outlines the possible operating region of a device or system under various constraints, which allows this quantification method to assess network-compliant energy flexibility, unlike other methods that often overlook network limitations. Utilising this framework, the main flexibility metrics – capacity, ramp, duration, and cost – are evaluated using features related to capability, feasibility, ramp, duration, economics, technical aspects, and commercial factors. These flexibility features are represented in an active-reactive power space (PQ-space). The total flexibility is calculated using Minkowski summation across the individual DER P-Q regions.

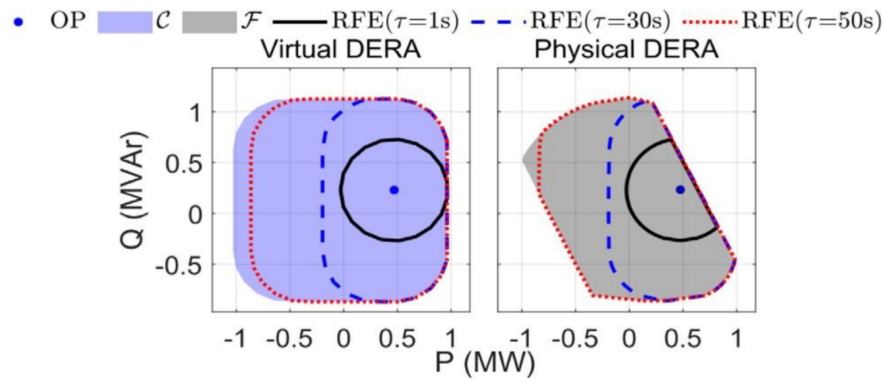

Figure 3.2. Nodal operating envelopes in PQ plane (capability – the combination of red and blue regions, feasibility – blue region in NOE figure) [125]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web verions of this article).

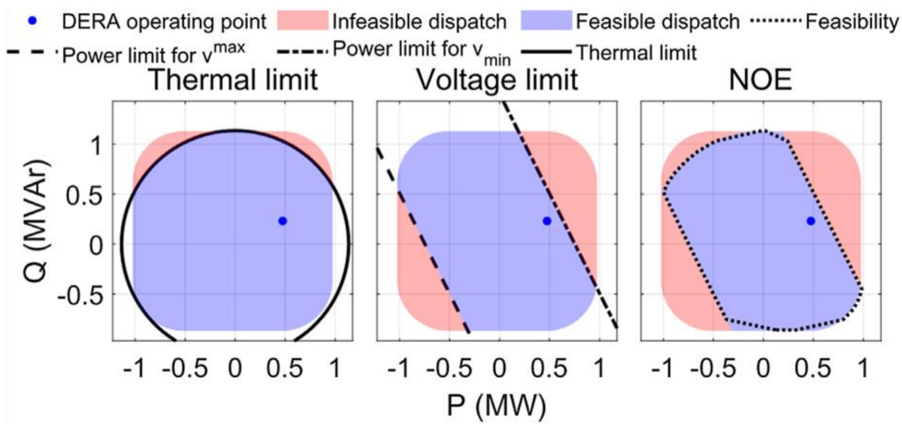

Figure 3.3. Ramping flexibility (OP – operational point, C – capability region, F – feasibility region, RFE – ramping flexibility envelope, τ – ramp time) [125].

This approach differentiates between virtual and physical flexibility. Virtual flexibility refers to the *capability* operation region of the DER to deliver flexibility without being limited by network constraints encountered in actual implementation. Physical flexibility, on the other hand, is the *feasibility* operation region that results when the *capability* region is restricted by network and other constraints, as illustrated in Figure 3.2.

Various techno-economic aspects of distributed energy resource aggregation (DERA) flexibility can be measured as potential operating zones by utilising other nodal operating areas. For instance, the *ramping flexibility* can be quantified with contours on these regions that display the maximum active and reactive power that can be utilised depending on the needed ramp rate, as illustrated in Figure 3.3.

These envelopes can also be designed to quantify additional features of flexibility. *Duration flexibility* indicates how long the activation of flexibility can be maintained. *Economic flexibility* refers to the costs associated with activating flexibility for a given timeframe. *Technical flexibility* involves the capacity to alter the current operational state concerning time and duration limitations. Finally, *commercial flexibility* is essential for engaging in the market while considering the techno-economic factors of time, service duration, and expected clearing prices. Example envelopes illustrating these flexibility traits can be found in [125].

3.1.2 Quantification parameters

In various studies, a consistent approach to quantifying energy flexibility is frequently absent. Rather, flexibility is assessed through a variety of different parameters that describe electrical, temporal, comfort, and cost aspects. The parameters utilised to measure energy flexibility are outlined in Table 3.2. It has been noted that flexibility can be measured across three primary dimensions: power [kW], energy [kWh], and time [h]. Depending on the specific application or context, these dimensions may illustrate entirely different attributes; for instance, both duration and regeneration time are considered time-related factors.

- The power dimension refers to the power capacity [kW] of flexible loads. This is the primary factor for flexibility sources that have power regulation features, like adjustable lighting. Parameters related to power dimension identified in the literature include instantaneous power flexibility, maximum power, mean power, maximal charging power, and power capacity.
- The energy [kWh] dimension is the primary factor for loads that can be stored or flexible loads that can be shifted in volume. Various energy parameters identified in the literature include shiftable energy, energy reduction, energy capacity, storage capacity, and available storage capacity.
- The dimension of time [h] is crucial for measuring flexible loads that can be scheduled or have a variable profile. For instance, the start and end times of the washing machine, along with the length of its operational cycle. The literature includes various time characteristics, including duration, comfort capacity, regeneration time, comfort recovery, maximum curtailment duration, and availability period.

In addition to the primary three dimensions for measuring flexibility, there are various other methods to quantify flexibility using combined, relative, or alternative approaches.

- Combined parameters seek to quantify flexibility based on two variables, such as the power shifting capability that illustrates the relationship between the shiftable power and the time length it can be shifted, or a cost curve that represents the volume of shiftable energy along with its related costs.

- Relative parameters quantify flexibility as a ratio of two characteristics: self-consumption, which indicates the percentage of demand met by onsite generation, or storage efficiency; relative peak reduction; demand response potential; and the state of charge (SOC) of batteries.
- Relative parameters quantify flexibility as a ratio of two characteristics, these are self-consumption, which is the proportion of demand covered by onsite generation or storage efficiency, relative peak reduction, demand response (DR) potential, and battery SOC.
- Other parameters identified in the literature include those that do not fall into any of the above mentioned categories, such as coefficient of variation of power, ramping rate, frequency of operation, consistency of operation, peak time operation and a score indicating the flexibility of a system on a scale from 0 to 1.

Table 3.2. Flexibility quantification parameters in the literature.

Type	Parameter	Descriptions as given in publications	Ref.
Power [kW]	Instantaneous power flexibility	The potential power flexibility of TES and power-to-heat in any case of charging, discharging, or idle mode	[126]
		The peak response after a trigger signal is sent	[127]
	Maximum power	The corresponding mean power for the duration of an activation	[127]
	Mean power	The EV station maximal charging power*	[128]
	Maximal charging power	Average lighting power curtailment during the curtailable duration	[129]
	Average power curtailment	How much power can be delivered as flexible power	[130]
	Power capacity		
Energy [kWh]	Available storage capacity	The amount of energy that is shifted during optimal control	[126]
		The amount of energy that can be added to the storage system, without jeopardizing comfort, in the time-frame of an ADR-event and given the dynamic boundary conditions	[131]
	Shiftable energy	The energy content below the curve; this energy can be consumed by the pool over the period of activation	[127]
	Energy reduction	How much energy can be reduced during a whole day	[129]
	Energy capacity	How much energy can be delivered during the flexibility action	[130]
	Storage capacity	The energy that can be added to the building thermal mass during a specific DR action	[132]
Time [h]	Duration	The time until the electricity consumption of the activated pool falls below the level of baseline operation	[127]
	Regeneration time	The time additional to the duration until the power consumption of the pool is back to	[127]
	Availability period	normal	[128]
	Maximum curtailment	The time when EV is available for flexible usage*	[129]
	duration	The sum of time in which the curtailment is possible during a whole day	[130]
	Comfort capacity	How long the response can be sustained before the comfort limits are reached	[130]
	Comfort recovery	How long the building requires to restore the nominal comfort	

Combined	Power shifting capability [kW, h]	The relation between the change in power and the time length that this shift can be maintained, considering the future boundary conditions	[131]
	Cost curve [kWh, EUR]	The amount of flexibility (shiftable energy) and its associated cost	[133]
Relative	Self-consumption [%]	Proportion of increased demand covered by onsite generation during DR action	[132]
	Storage efficiency [%]	A measure of the energy cost associated with the specific DR action	[132]
		The ratio between discharging and charging events over the entire 24 h control horizon	[126]
		The fraction of the heat stored during the DR event that can be used subsequently to reduce the heating power needed to maintain thermal comfort	[131]
	Battery SOC (%)	The state-of-charge of the (EV) battery*	[128]
	Relative peak reduction [-]	Compares the deviation from the average of the minimum lighting power profile to the reference scenario	[129]
	DR potential (%)	Potential power change during DR operation compared to baseline power consumption*	[134]
Other	Coefficient of variation of power curtailment [-]	Determines whether the lighting system can provide a stable power curtailment capacity or a fluctuating capacity	[129]
	Ramping rate [kW/min]	How fast the building reacts	[130]
	Frequency of operation [0-1]	The ratio of the number of days that an appliance has been activated compared to the total number of historical days	[135]
	Consistency of operation [0-1]	The extent to which a user's behaviour is deterministic or stochastic across subsequent days	[135]
	Peak time operation [0-1]	The energy consumption during the DR timeframe across historical days using min–max normalisation	[135]
	Potential score [0-1]	Flexibility "score" based on the above 3 parameters	[135]

* Own descriptions based on the context of the work since the definitions were not provided in those publications

3.2 Forecasting of demand-side energy flexibility

For aggregators to engage in flexibility markets, they must evaluate the resources within their portfolio, specifically the available aggregated energy flexibility. Considering that contracts in flexibility markets are established prior to the actual delivery date, aggregators need to determine the volume of flexibility they can provide and which flexibility requests to bid on by forecasting the available flexibility in the future while accounting for reasonable uncertainty. However, forecasting flexibility is a complex endeavour, as it is affected by customer behaviour, consumption trends, weather conditions, and other influencing factors, making precise modelling challenging. Artificial intelligence (AI) is increasingly being incorporated into the management of power systems to improve the accuracy of forecasting and optimise flexibility. Recent studies [Paper V] have shown that predictive models powered by AI enhance demand response, load forecasting, and the management of distributed energy resources, thereby becoming essential tools for aggregators overseeing flexibility resources. To avoid facing penalties for failing to deliver the appropriate amount of contracted flexibility, aggregators also need to predict how customers will respond to flexibility activation signals (such as price signals) to ensure that the correct volume of flexibility is indeed activated.

There are limited publications available that focus specifically on forecasting residential demand-side energy flexibility. The majority of research appears to concentrate more on load forecasting [136], [137], [138], [139], which does not directly equate to flexibility forecasting. The flexibility of data centres that participate in demand response initiatives is assessed in [140]. The flexibility associated with virtual power plants is forecasted through the application of machine learning techniques in [141]. The potential for flexibility in demand response within the industrial sector is analysed in [142]. Load forecasting related to industrial machinery is addressed in [143]. A general assessment of flexibility potential is investigated using long-term historical data in [122], [144], [145] or through surveys gauging customer readiness to engage in demand response programs in [146], [147].

According to [136], having smart meter coverage of just 5% is sufficient to generate data for accurately forecasting the flexibility of a group of aggregated customers. Additionally, predicting the flexibility profile of an aggregated group is significantly easier than forecasting the flexibility of individual customers because of their stochastic nature [136], [148], [124].

An overview of the studies concentrated on flexibility forecasting is provided in Table 3.3, where they are categorised by the type of forecasting model used:

- Deterministic models operate under the assumption of certainty in the input parameters, which means they rarely provide uncertainty assessments in their predictions.
- In probabilistic models, the objective of forecasting is to represent the distribution of potential available flexibility rather than to predict a specific value, inherently incorporating prediction uncertainty.
- Machine learning models are utilised to analyse customer behaviour during demand response and regular operations to assess the potentially available flexibility.

In existing research, various approaches have been employed for predicting flexibility, corresponding to the initial two checkmark columns on the left in Table 3.3. For instance, some studies focus on predicting flexibility based on a price signal, framing the forecasting question as "What price incentive should be provided for certain hours ahead to achieve the required amount of flexibility?" rather than "How much flexibility will be available during specific hours in the future?". Research utilising this method frequently views forecasting as an optimisation challenge and often includes finding an optimal schedule for devices.

Other approaches discussed in the literature aim to predict flexibility through real-time simulations [149] or using historical data. Studies that employ this technique typically seek to gather insights regarding both controllable and uncontrollable loads from previously recorded measurements. The forecasting of flexibility related to shiftable loads (like washing machines, tumble dryers, and dishwashers) as well as thermostatically controlled loads (including domestic water heaters, space heating, and HVAC systems) is most frequently addressed in the literature. In contrast, forecasts related to storable loads, such as battery storage and residential electric vehicles, are infrequently found in existing studies.

Table 3.3. Flexibility forecasting models used in the literature.

Forecasting model type	Specific model	In response to a price signal	Based on historical data	Shiftable loads	Thermostatically controlled loads (TCL)	Battery storage	Electric vehicles (EV)	National level (broad range of sources)	Ref.
Deterministic models	Mixed Integer Linear Programming (MILP)	✓			✓				[150]
		✓		✓	✓	✓	✓	✓	[151]
		✓	✓					✓	[152]
		✓		✓	✓				[153]
		✓		✓			✓		[154]
		✓	✓	✓	✓				[155]
	Algorithmic method		✓		✓				[156]
Probabilistic models	Chance-Constrained (CC)	✓	✓					✓	[152]
	Autoregressive integrated moving average (ARIMA)		✓		✓				[157]
		✓	✓				✓		[158]
			✓		✓				[159]
	Data analysis based		✓		✓				[160]
Machine learning models	Neural Networks (NN)		✓	✓	✓				[161]
			✓		✓				[162]
	Support Vector Machine (SVM)	✓	✓	✓	✓				[163]
	Support Vector Data Description (SVDD)				✓	✓			[164]
	Logistic Regression	✓	✓	✓					[165]
	Piecewise-linear regression		✓		✓				[166]

3.3 Conclusions

This chapter offers an analysis of existing methods for quantifying demand-side energy flexibility, noting both their strengths and weaknesses. Energy flexibility is a dynamic concept that encompasses adjusting energy consumption or generation in response to external signals, such as market prices or grid demands. The reviewed literature highlights the need for proper quantification methods.

Existing approaches often oversimplify flexibility's complex and dynamic nature by relying on static or single-value metrics. Significant progress has been made with the development of flexible envelopes and nodal operating envelopes. These limitations highlight the need for more advanced methodologies, such as power-duration curves, which better capture flexible loads' non-linear and time-dependent behaviours. Characterising rebound effects and their implications for energy savings and grid stability introduces a critical dimension frequently overlooked in traditional models.

The review also examined the role of flexibility forecasting. Accurately predicting available flexibility is crucial for integrating demand-side flexibility into energy markets. However, the literature review revealed a notable lack of publications in this field.

In summary, this chapter highlighted the limitations of existing quantification methods and emphasised the need for a new approach that tackles the asymmetry and non-linearity of flexibility. These insights provide the grounds for the development of a power-duration curve method, which will be presented in the next chapter as a more thorough and practical tool for quantifying energy flexibility.

4 Development of energy flexibility quantification method

Building upon the insights gained in the previous chapter, this chapter introduces a novel approach to quantifying energy flexibility using power-duration curves [Paper I]. The proposed method addresses key challenges in flexibility assessment, particularly the non-linear and asymmetric nature of flexible loads. By mapping the relationship between power and duration, this approach provides a more accurate and practical representation of energy flexibility, which can be applied to various flexible loads such as space heating, electric water heaters, and battery storage systems and various markets such as reserve or day-ahead markets.

4.1 Flexibility power-duration curves

Energy flexibility can be perceived as a resource that can be used and replenished. It is utilised through demand response and then restored during the subsequent rebound effect. Figure 4.1 illustrates how various power levels and durations can decrease demand using aggregated energy flexibility. When the maximum power of a specific portfolio is utilised, it leads to the most significant decrease in demand but can only be maintained for a short period. Conversely, a modest activation produces the opposite effect. This offers insights into how energy flexibility functions as a resource – the more it is utilised, the faster it is exhausted. To quantify aggregated energy flexibility, this thesis proposes a new approach. The approach focuses on mapping a curve that describes the relationship between the power and duration of potential flexibility activations.

Aggregators might obtain a more comprehensive picture of their energy flexibility resources by employing this quantifying technique. This approach is adaptable, allowing aggregators to participate in a variety of energy markets, each with its own requirements regarding both the amount and the duration of deliveries. For example, only need to activate their flexibility for a maximum of fifteen minutes in reserve markets, but activations for day-ahead wholesale markets might extend over several hours. It is apparent that for long-duration wholesale market activations, the aggregator would not be able to maintain the same high-power activations as in the case of the reserve market.

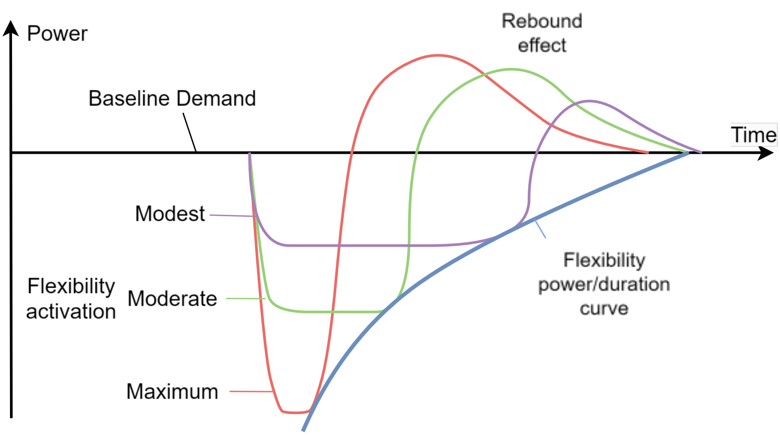

Figure 4.1. Illustration of flexibility activations at different power levels.

4.2 Proposed quantification method

Figure 4.2 presents an outline of the proposed quantification method. The first step involves importing relevant data that impacts the usage of flexible devices. For space heating, meteorological data such as outdoor ambient temperature and solar irradiance forecasts influence the demand for heating energy. As for other flexible devices like electric water heating units, the hot water usage profile needs to be imported.

In the second step, it is crucial to choose a suitable model for each type of device and determine its parameters. Modelling the behaviour of devices is important to ensure that the appliances remain within the comfort boundaries set by consumers when the flexibility is activated. Thermostatically controlled loads (TCLs), such as a building's heating system or a EWH unit, can be modelled using a thermal resistive-capacitive model.

The third step involves modelling the appliance's business-as-usual (BaU) operation case to determine the electrical demand profile under normal operation without flexible activation. This step can be considered part of the baseline estimation in the quantification process.

In the fourth step, potential flexibility can be quantified based on the demand profiles determined in the previous step, the models of flexible devices, and the state of each flexible device within their comfort ranges. This involves simulating flexibility activations of devices at each time step, meaning turning devices on/off until the comfort boundaries are reached.

In the final, fifth step, the power-duration curves can be constructed by knowing the devices' power and the duration that the flexibility can be activated.

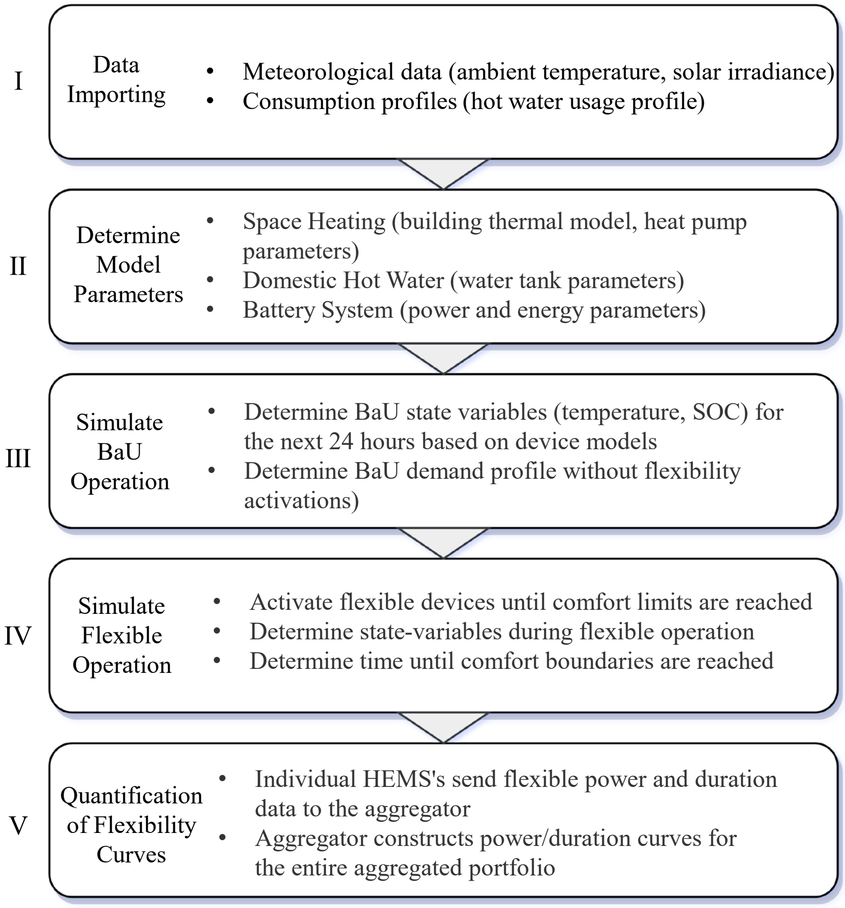

Figure 4.2. The quantification process of the proposed method.

4.3 Modelling of space heating

It is crucial to accurately model a building's thermal behaviour in order to quantify a heating system's energy flexibility. This is necessary because indoor temperature must always remain within the comfort range of the occupants. As a result, the energy required for heating can vary from building to building, taking into account the building's thermal insulation and thermal mass. Some need more energy for heating, while others can go for extended periods with the heating turned off.

This study used a Resistive-Capacitive (RC) model to model buildings' thermal behaviour. Unlike more detailed white-box models, the RC model is a grey-box model that approximates building parameters related to their thermal dynamics. Similar to electrical circuits with resistors and capacitors, the thermal RC model incorporates different building components' thermal capacitances and resistances (U-values).

The 3R2C thermal model used in the study consists of three thermal resistors and two thermal capacitors. It considers the building envelope (external walls), the windows, and the internal thermal mass (interior walls, furniture, and air) as the three primary components of a building.

Figure 4.3 shows the simplified thermal network design applied in this work. It shows that the outdoor temperature T_{out} affects the indoor temperature T_{in} through both the building envelope and the windows. Additionally, it assumes that the solar effect only impacts the indoor temperature through the windows. The study also assumes that the indoor temperature remains uniform throughout the building. The inputs, outputs, and parameters of the thermal RC model are shown in Table 4.1.

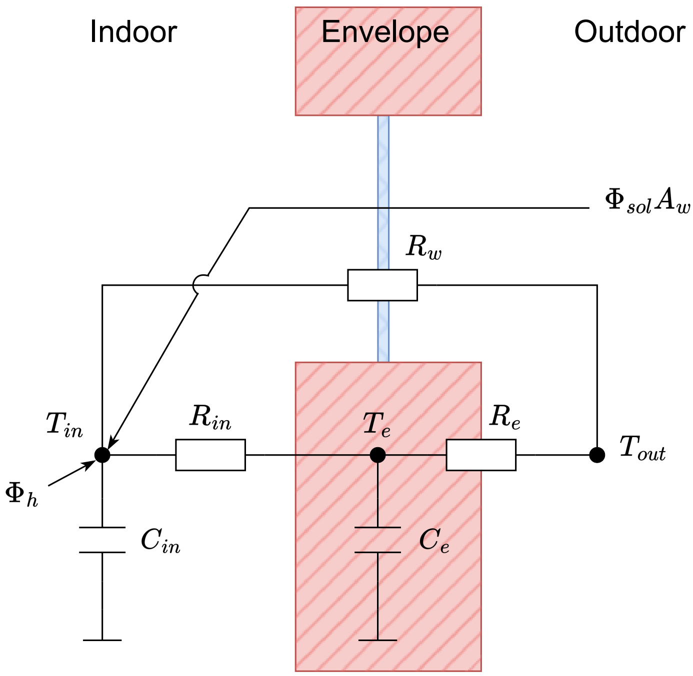

Figure 4.3. RC thermal networks of a building.

Table 4.1. Description of Thermal Network Parameters.

	Symbol	**Description**
Inputs	T_{out}	Ambient temperature, °C
	ϕ_{sol}	Global horizontal solar irradiance, $\mathrm{W/m^2}$
	ϕ_h	Heating power, W
Outputs	T_{in}	Indoor air temperature, °C
	T_e	Envelope temperature, °C
Parameters	R_e	Envelope thermal resistance, °C/W
	C_e	Envelope thermal capacitance, J/°C
	R_{in}	Inner mass thermal resistance, °C/W
	C_{in}	Inner mass thermal capacitance, J/°C
	R_w	Window thermal resistance, °C/W

The generic heat-balance equation (3.1) can be used to create a first-order differential equation for each node n in a thermal system with N elements:

$$C_n \frac{dT_n}{dt} = \sum_{i \in N} \frac{T_i - T_n}{R_i} \Phi_n \tag{4.1}$$

where C_n and T_n represent the thermal capacitance and the temperature of node n, respectively, R_i represents the thermal resistance between two connected nodes i and n, and Φ_n represents the total heat fluxes applied to node n [167].

Equation (4.1) illustrates how the number of components taken into account can affect the complexity of a thermal RC model. By combining elements from several architectural components – such as the roof, the construction of exterior and interior walls, and insulating layers – a more comprehensive model may be produced. In essence, therefore, RC thermal networks are models that can consist of different arrangements of resistors and capacitors that represent various architectural components.

The differential equations describing the temperature of the interior mass (4.2) and the envelope (4.3) of a building may be obtained by applying the heat-balance equation (4.1) to the thermal RC network structure shown in Figure 4.3.

$$\dot{T}_{in} = \frac{1}{R_{in}C_{in}} T_e - \left(\frac{1}{R_{in}C_{in}} + \frac{1}{R_w C_{in}}\right) T_{in} + \frac{1}{R_w C_{in}} T_{out} + \frac{1}{C_{in}} \phi_h + \frac{1}{C_{in}} \phi_{sol} A_w \tag{4.2}$$

$$\dot{T}_e = -\left(\frac{1}{R_{in}C_e} + \frac{1}{R_e C_e}\right) T_e - \frac{1}{R_{in}C_e} T_{in} + \frac{1}{R_e C_e} T_{out} \tag{4.3}$$

Converting the above differential equations into difference equations (4.4) and (4.5) allows modelling of building's thermal behaviour for each timestep.

$$\begin{aligned} T_i(t+1) = T_i(t) + \Bigg(& \frac{T_e(t) - T_i(t)}{R_i C_i} + \frac{T_a(t) - T_i(t)}{R_w C_i} + \frac{\Phi_{sol}(t) A_w}{C_i} \\ & + \frac{\Phi_h(t)}{C_i} \Bigg) \Delta t \end{aligned} \tag{4.4}$$

$$T_e(t+1) = T_e(t) + \left(\frac{T_i(t) - T_e(t)}{R_i C_e} + \frac{T_a(t) - T_e(t)}{R_e C_e} \right) \Delta t \tag{4.5}$$

The thermal behaviour of buildings is affected by different factors such as their size, insulation level, construction materials, window-to-wall ratio, number of inner walls, and more. Since these factors vary from building to building, it's important to simulate various types of buildings when studying aggregated energy flexibility. However, estimating the parameters of an RC model for a specific building is a complex process. To the best knowledge of the author, there is no publicly available database that includes the necessary number of actual building thermal network parameters for simulating aggregated control.

Therefore, it is necessary to generate these parameters based on existing guidelines. From Table 4.1, it can be seen that six different parameters for each building need to be determined to model its thermal behaviour. Table 4.2 provides typical thermal network values for residential buildings categorised by weight class. The range of values for typical building envelopes was determined in [168] through a first-principles analysis of various building construction materials. The standard ISO 52016-1:2017 [169] presents typical values for the inner thermal mass of buildings. The weight class of a building describes its construction materials. For example, the exterior walls of lightweight buildings consist of stucco, insulation, and plaster/gypsum. Medium-weight buildings use brick, air space, insulation, and gypsum, while heavy-weight buildings use brick, heavyweight concrete, insulation, and gypsum. We assumed that the thermal resistance of windows corresponds to that of typical double-glazed windows, while the thermal capacitance of windows is considered negligible.

Table 4.2. Typical thermal network parameters for different types of residential buildings.

Envelope Thermal Network Parameters		
Class	$R_e\left(\frac{\mathrm{m^2C}}{\mathrm{W}}/\mathrm{m^2}\right)$	$C_e\left(\frac{kJ}{\mathrm{m^2C}}\cdot\mathrm{m^2}\right)$
Light-Weight	$3.1498/A_e$	$76.852 \cdot A_e$
Medium-Weight	$3.8238/A_e$	$183.724 \cdot A_e$
Heavy-Weight	$2.1917/A_e$	$402.102 \cdot A_e$
Windows	$0.8333/A_w$	0
Inner Mass Thermal Network Parameters		
Class	$R_i\left(\frac{\mathrm{m^2C}}{\mathrm{W}}/\mathrm{m^2}\right)$	$C_i\left(\frac{kJ}{\mathrm{m^2C}}\cdot\mathrm{m^2}\right)$
Light-Weight	$0.13/A_{fl}$	$110 \cdot A_{fl}$
Medium-Weight	$0.13/A_{fl}$	$165 \cdot A_{fl}$
Heavy-Weight	$0.13/A_{fl}$	$260 \cdot A_{fl}$
Building Size Parameters		
Floor Area, A_{fl}	$uniform(50, 200), m^2$	
Building Height	$uniform(5, 12), m$	
Window-to-Wall Ratio	$uniform(20, 50)$, %	

4.4 Modelling of domestic electric water heaters

In order to accurately quantify the energy flexibility of electric water heaters (EWHs), it is necessary to develop a model that captures their thermal behaviour. This approach guarantees that the consumer's comfort is maintained even during flexible operation. It is essential that the hot water temperature stays within the specific ranges mandated by the homeowners to ensure their comfort and willingness to participate in demand response programs.

The thermal behaviour of EWHs was modelled using an RC-thermal network. This grey-box model loosely incorporates the parameters related to EHWs' thermal dynamics. Thermal RC models are analogous to electrical circuits with resistors and capacitors, which, in this case, represent the thermal resistance and thermal capacitance of different water tank elements.

In this thesis, a simple 1R1C model consisting of one thermal resistor and one thermal capacitor was considered. This simple model assumes that the water temperature inside the tank is homogeneous. Figure 4.4 illustrates the EHW model. The convective loss through the shell of the EWH is modelled using a resistor, and the thermal mass of the water inside the EWH is modelled using a capacitor. A current source is used to model the heating power, and a current sink is used to represent the thermal loss through hot water drainage, which is replaced by colder tap water.

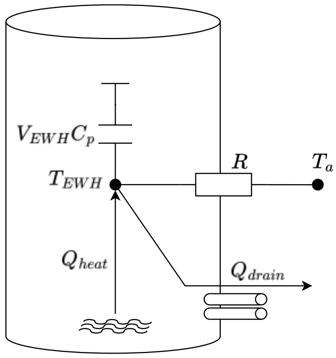

Figure 4.4. Thermal network model of EWHs.

The generic heat-balance equation (4.6) can be used to create a first-order differential equation for each node n in a thermal system with N elements:

$$C_n \frac{dT_n}{dt} = \sum_{i \in N} \frac{T_i - T_n}{R_i} \Phi_n \tag{4.6}$$

where C_n and T_n represent the thermal capacitance and the temperature of node n, respectively, R_i represents the thermal resistance between two connected nodes i and n, and Φ_n represents the total heat fluxes applied to node n.

The heat-balance equation can be applied to the thermal network in Figure 4.4 to derive the difference equation (4.7) that describes the water temperature of EWHs.

$$T_{EWH}(t+1) = T_{EWH}(t) + Q_{heat}(\mathrm{t}) - Q_{drain}(\mathrm{t}) - Q_{loss}(t) \tag{4.7}$$

where the positive heat flux from electric heating that increases the water temperature is $Q_{heat}(t) = \mathrm{P}_{EWH}(t)$. The electrical heating power was assumed to scale with the tank's size, starting from 1.5 kW to 2.5 kW in 0.5 kW steps.

The negative heat flux from hot water drainage (4.8) that reduces the water temperature is:

$$Q_{drain}(t) = \frac{V_{flow}(t) C_p \left(T_{EWH}(t) - T_{inflow}(t)\right)}{C_p V_{EWH}} \tag{4.8}$$

where the volume of water being replaced in the tank is $V_{flow}(t)$, the specific heat capacity of water is C_p, the volume of the water tank is V_{EWH}, and the temperature of inflow water is $T_{inflow}(t)$.

The thermal mass of EWH units is dependent on the size of the water tanks. A total of 1000 EWH units were modelled with varying sizes of 50 L to 200 L capacity with 50 L step (250 EWH units for each step). The specific heat capacity of water was assumed to be 4182 $\mathrm{J/(kg \cdot °C)}$. The inflow water temperature was assumed to be 15 °C. The hot water usage data was generated for each EWH using DHWCALC software that samples from statistical distributions derived from real-world measurements of residential hot water consumption [170].

Table 4.3. Model parameters of EWHs.

	Symbol	Description
Inputs	T_a	Room temperature, °C
	T_{inflow}	Inlet water temperature, °C
	P_{EWH}	Heating power, W
	V_{flow}	Hot water consumption, L/min
Parameters	U	U-value of tank insulation, $\mathrm{WK^{-1}m^{-2}}$
	A	Surface area of the water tank, $\mathrm{m^2}$
	C_p	Specific heat capacity of water, $\mathrm{J/(kg \cdot °C)}$
	V_{EWH}	Volume of the water tank, L
Output	T_{EWH}	Hot water temperature, °C

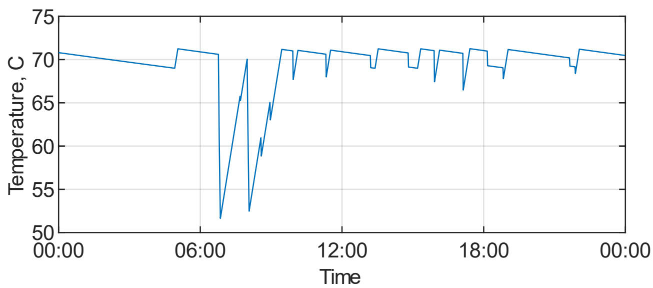

Figure 4.5. Water temperature of one simulated EHW.

The negative heat flux from convective loss through the shell (4.9) that reduces the water temperature is:

$$Q_{loss}(t) = \frac{UA\big(T_{EWH}(t) - T_a(t)\big)}{C_p V_{EWH}} \tag{4.9}$$

where the insulation of the shell is given with a U-value, the area of the shell is A, and the ambient room air temperature is $T_a(t)$. The U-value was taken as 0.66 $\mathrm{WK^{-1}m^{-2}}$ that is typical for water tanks [171], and the water tank surface area was assumed to be of cylindrical shape. The room ambient temperature was assumed to be 20 °C. The parameters of the EWH model are summarised in Table 4.3.

The Business-as-Usual (BaU) operation of EWH was modelled as a typical hysteresis on-off control that turned the heating on when the temperature dropped 1 degree below the setpoint and turned the heating off when the temperature rose 1 degree above the setpoint. The water temperature set points were sampled from 60 to 75 °C, with 5 °C steps to accommodate different consumer requirements. Using the model described above, the BaU operation of EWHs was simulated. An example of the water temperature trajectory of one simulated EHW is shown in Figure 4.5. It can be seen that during the morning hours, there are two large drops in the temperature when people often shower and multiple smaller drops throughout the day from faucet usage. The aggregated electricity demand of 1000 EWHs is shown in Figure 4.6.

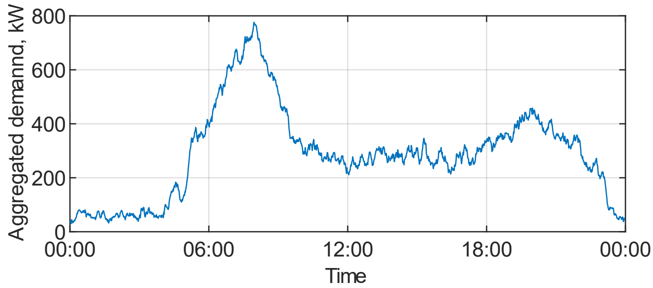

Figure 4.6. Aggregated electricity demand of 1000 simulated EHWs.

4.5 Modelling of battery energy storage system

Local on-site battery energy storage systems (BESS) are bound to become another important source of energy flexibility in future residential buildings. BESS are usually not installed as standalone devices except for universal power supply (UPS) systems. Thus, a combination of 1000 PV and BESS systems were modelled.

A rule-based controller was used for the BaU operation of the BESS system. The BaU algorithm works by storing the excess PV energy during a surplus time when solar generation is higher than consumption until the state-of-the-charge (SOC) of the battery reaches 100%, after which the excess PV power is exported. The release of energy happens during the solar deficit time when consumption is higher than PV production until the SOC reaches 20%, after which the deficit energy is imported. This is a typical residential PV and BESS system control which regulates BESS usage based on the energy flows through the connection point and the BESS's state of charge (SOC).

The battery systems were modelled using the typical battery energy balance equations (4.10) and (4.11).

$$E_{BESS}(t) = E_{BESS}(t-1) + \mu_c E_{BESS,c}(t) - \frac{E_{BESS,d}(t)}{\mu_d} \tag{4.10}$$

$$SOC(t) = \frac{E_{BESS}(t)}{E_{BESS,max}} \tag{4.11}$$

where the energy stored within the BESS is given with $E_{BESS}(t)$, the energy stored or withdrawn through charging or discharging are $E_{BESS,c}(t)$ and $E_{BESS,d}(t)$, the charging and discharging efficiencies are μ_c and μ_d, and the capacity of the BESS is $E_{BESS,max}$.

The parameters of a Tesla Powerwall 2 were used for the battery system, which has an energy capacity of 13.5 kWh, charging and discharging power of 5 kW, and charging and discharging efficiencies of 95% (round-trip efficiency of 90%).

This simulation requires the inclusion of solar generation profiles and residential building energy demand profiles to determine when there is an excess or a deficit of solar generation. The PV generation profiles were taken from measurements of a 4.2 kW PV system located in Estonia, Tallinn, on the 1st of April 2020 [172]. The demand profiles of 1000 residential buildings were generated using the "CREST domestic electricity demand model" [173]. Figure 4.7 shows the PV production data and the generated demand profile of one of the buildings.

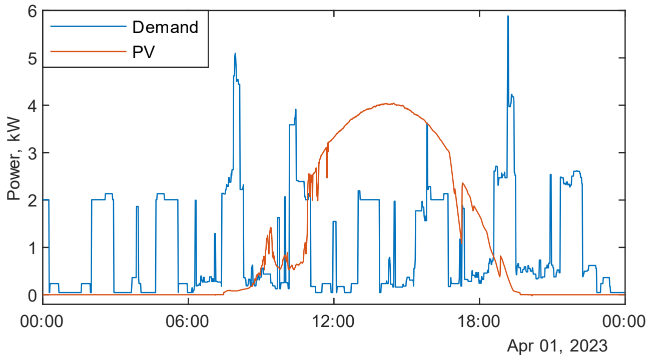

Figure 4.7. Consumption and PV generation data.

4.6 Conclusions

This chapter introduced a new method for quantifying energy flexibility through the use of power-duration curves, offering a dynamic and scalable way to capture the key attributes of energy flexibility. The developed approach addresses the limitations of existing single-value metrics by considering the non-linear, time-dependent, and asymmetric nature of flexibility. This advancement enables a more precise representation of flexibility potential, offering valuable insights for aggregators and grid operators.

The flexibility power-duration curve method provides a framework for quantifying flexibility in different scenarios and types of loads, such as residential heating, water heaters, and battery storage systems. By connecting flexible power capacity with the duration of activation, this method reflects the dynamic relationship between these factors, making it suitable for both short-term and long-term flexibility uses. This characteristic enhances its applicability for demand response programs, reserve markets, and balancing services, ensuring it can meet diverse operational and market needs.

The quantification method was described step-by-step, and in the next chapter 5, a simulation-case study is conducted to illustrate its implementation to quantify the aggregated energy flexibility of space heating, electric water heaters, and battery systems.

5 Simulation case-study

This chapter presents a simulation-based case study focusing on aggregated flexibility from mainly residential heating but also electric water heaters and battery systems to illustrate the process of employing the proposed flexibility quantification method. The case study demonstrates the practical application of power-duration curves and evaluates their effectiveness in representing energy flexibility. The analysis also considers rebound effects and their implications for demand-side management, emphasising the need for advanced quantification techniques.

5.1 Aggregation framework

To showcase the benefits of the proposed quantification method, a simulation-based case study was conducted to quantify the aggregated energy flexibility of 1000 buildings using heat-pump based space heating. The aggregation framework illustrated in Figure 5.1 can be applied to real-world scenarios, although some simplifications were made for the sake of the simulation. The framework comprises two main components: the aggregator and the Home Energy Management Systems (HEMS) of each building. HEMS takes inputs from weather forecasts, heat pumps, and homeowners (step 1 of the quantification). For simulation purposes, data from PVGIS was used, although, in reality, ambient temperature T_a and solar irradiance (GHI) would be obtained from external cloud servers. HEMS receives indoor temperature T_{in} and electricity consumption P_{el} data via a datalink with the heat pump. Homeowners can also input their comfort preferences by setting upper T_{max} and lower T_{min} temperature limits for the indoor environment.

The HEMS is designed to carry out three primary tasks: identifying the thermal model, simulating business-as-usual scenarios, and simulating flexible operations. First, the thermal model needs to be identified for each building in a real-world implementation (step 2 of the quantification). However, for simulation purposes, the RC parameters are sampled from guidelines and publications. Based on the identified thermal model, the weather forecasts, heat pump telemetry, and the homeowners' comfort requirements, a BaU simulation is performed to determine the baseline behaviour without any flexibility activations (step 3 of the quantification). Once the baseline has been established, a flexibility activation simulation is performed to estimate the amount of time that the heating system may be turned on t_{upFlex} or off $t_{downFlex}$ until the comfort boundaries (step 4 of the quantification). Together with the baseline power profile P_{BaU}, these durations are sent to the aggregator, which enables it to map the flexibility curves.

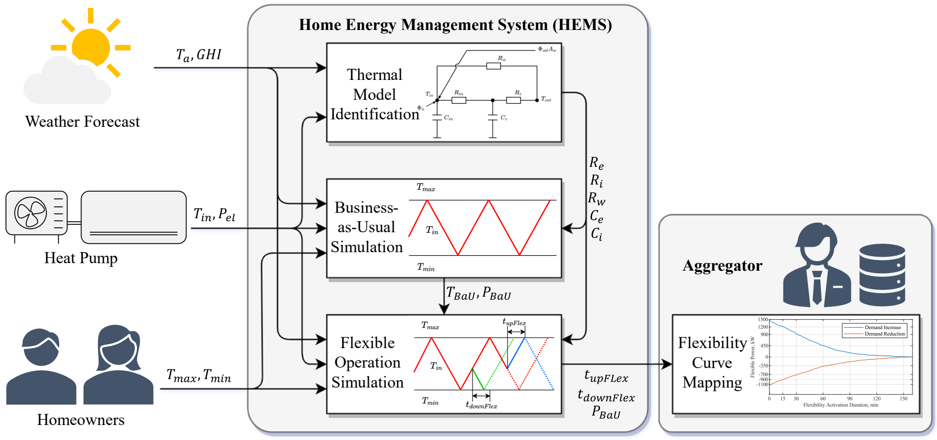

Figure 5.1. Overview of the aggregation framework.

5.2 Energy flexibility quantification

5.2.1 Space heating

This section will provide an example of how to use the proposed approach depicted in Figure 4.2 to assess aggregated energy flexibility for space heating.

The initial step in the quantification method involves importing relevant meteorological data regarding space heating. Weather data from PVGIS starting from April 2020 was used for the simulation. This date was selected because, as Figure 5.2 illustrates, it captures both the low outside temperature and solar heating elements that influence the amount of indoor heating used.

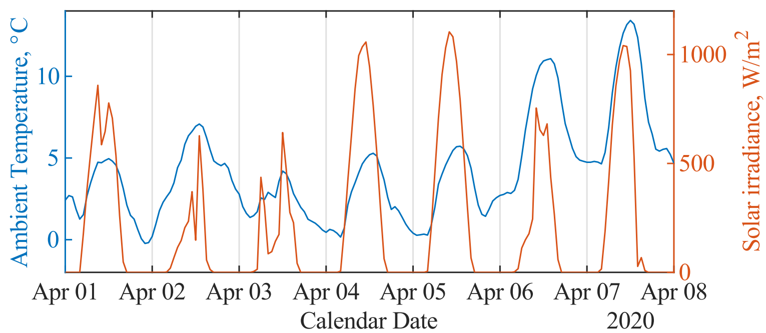

Figure 5.2. Meteorological data obtained from PVGIS [174].

In the next step of the quantification method, we model the thermal dynamics of buildings. The study uses a simple 3R2C thermal network, but for greater accuracy, the model can be made more complex by adding extra resistors and capacitors. Table 4.2 shows that all thermal network parameters are proportional to the floor area A_{fl}, exterior wall area A_e, or window area A_w. This means that by sampling typical values for building constructional parameters [175], [176], many different building thermal network parameters can be generated. Buildings of different sizes, with floor areas ranging from 50 to 200 square meters, building heights of 5 to 12 meters, and window-to-wall ratios of 20 to 50%, were sampled from a uniform distribution. The exterior envelope area A_e was calculated based on the floor area A_{fl} and building height, and the window area capacity was derived using the generated window-to-wall ratio. By generating different types of buildings, it is possible to simulate a portfolio that includes many different kinds of buildings with respect to their thermal characteristics.

The initial values for the heating system's on/off status, indoor temperature, and building envelope were determined by running a 0-day simulation. This was done to minimise the initial fluctuations in the simulation that result from random state parameter initialisation. The 0-day simulation began by setting the indoor and envelope temperatures to random values between 22 and 24 degrees Celsius, and the heating system's on/off state to a random value of 0 or 1. The results of the 0-day simulation were then used as the starting point for the subsequent flexibility simulations. The thermal heating power was assumed to be proportional to the building's floor area and varied between 6 kW and 12 kW. Additionally, the coefficient of performance (COP) of the heat pump was set to be between 3 and 4, taking into account devices from different manufacturers.

In the third step of quantification, the Business-as-Usual (BaU) scenario needs to be simulated to determine the baseline demand without any flexibility activations. The RC-thermal network models created in the previous step can be used to simulate the BaU scenario. Equations (4) and (5) allow us to simulate the temperature trajectories by knowing the initial interior temperature as well as the impacts of external elements like solar effects and the outside ambient temperature. In the BaU scenario, it is assumed that the target indoor temperature is set at 23 °C, with an on/off control deadband of plus or minus 1 °C. Ten distinct building temperature trajectories are shown in Figure 5.3, illustrating the differences in the time it takes for a building to heat up and cool down.

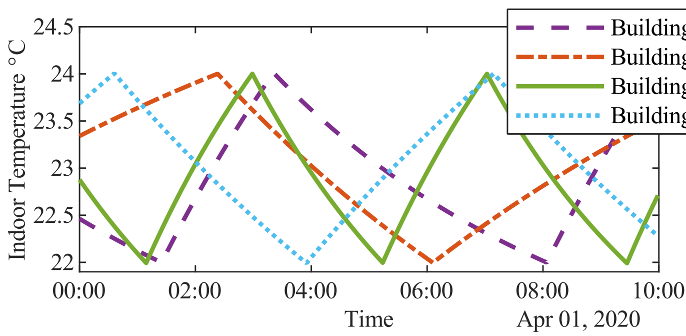

Figure 5.3. Examples of 4 simulated building temperature trajectories.

Figure 5.4 displays the demand profile for the BaU case. Comparing the graph to the ambient temperature in Figure 5.2 reveals that during the first five days of the week when the temperature ranges from +1 °C to +5 °C, the demand for 1000 heat pump units fluctuates between 850 kW and 1100 kW. Towards the end of the week, as the temperature increases, there is a noticeable reduction in electricity demand.

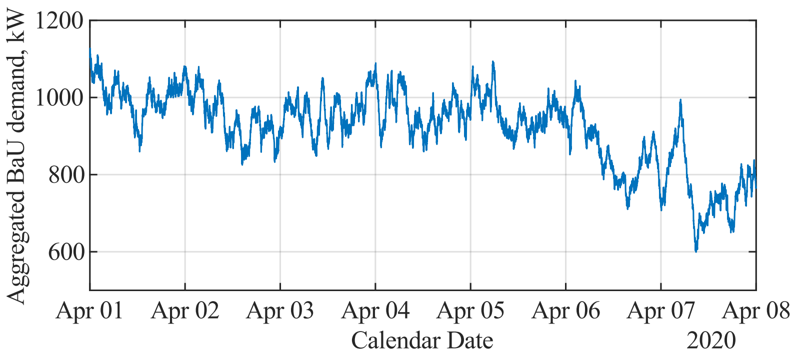

Figure 5.4. Aggregated demand of 1000 simulated heat pumps for BaU case.

After identifying the demand profile and on-off switching of the heat pumps in the BaU case, flexible operation is simulated. The flexibility provision is assumed to occur within the same temperature range as the BaU scenario (22–24 °C). For instance, if the ambient temperature in a building is 22.5 °C and the heat pump is turned off, activating it allows us to raise the temperature to 24 °C. If a homeowner chooses to exceed the BaU range and offers additional flexibility (up to 25 °C), then the duration aspect of the house's flexibility would be extended. The potential for flexibility in heating systems relies on the comfort preferences of the owners and their readiness to adjust them. In this thesis, we have established a strict requirement of a maximum deviation of ±1 °C from the setpoint.

Figure 5.5 illustrates this concept. The energy flexibility available in each building varies based on the proximity of the indoor temperature to the temperature boundaries at any given time. When the indoor temperature is near the upper boundary, there is limited flexibility to increase the demand because the heating can only be turned on for a short period. Conversely, there is more flexibility to turn off the heating. The reverse is true when the indoor temperature is close to the lower boundary.

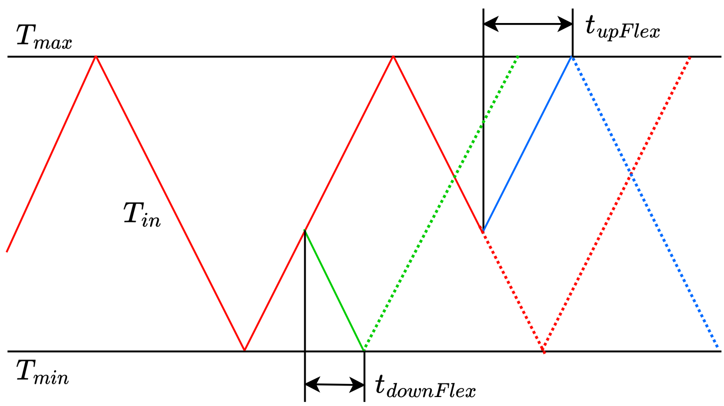

Figure 5.5. Illustration of temperature trajectories with flexible activation.

In the final step of the quantification process, all buildings provide the necessary data to the aggregator for quantifying aggregated energy flexibility. The data includes the on-off status of the heat pumps and the durations for which heating can be turned on or off until the temperature comfort boundaries are reached. Using this information, the aggregator can create two curves that describe the potential flexibility to increase or decrease the demand, as shown in Figure 5.6. Since the aggregator does not have access to the demand profiles, interior temperatures, or boundary levels, this method guarantees a better level of privacy.

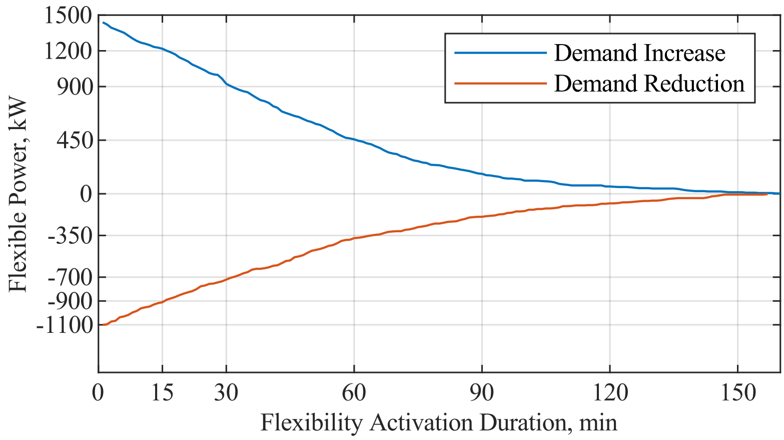

Figure 5.6. Aggregated flexibility power-duration curves.

Aggregators can obtain valuable knowledge about the energy flexibility of their portfolios and make better decisions regarding how to use that flexibility by employing the quantification approach developed in this thesis. For example, an aggregator who is focused on reserve markets, may be interested in activations that last up to 15 minutes. As seen in Figure 5.6, based on the previously discussed scenario, there is potential flexibility to increase or reduce the demand by 1200 kW and 900 kW for 15 minutes. On the other hand, if the aggregator is focused on day-ahead markets and aims to provide flexibility for 60 minutes, they will notice that the potential aggregated energy flexibility to increase or reduce demand has dropped to 450 kW and 350 kW. It's important to note that flexible power not only reduces with longer activation but is also asymmetrical, which may be relevant for markets that require symmetrical bids. Additionally, flexible power can be visualised in the context of flexible energy, as shown in Figure 5.7. This visualisation allows us to see how much flexible energy is available to increase or decrease consumption based on the activation duration.

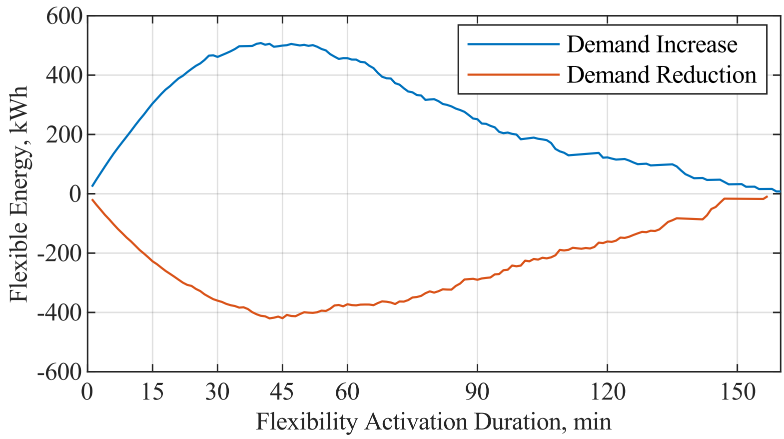

Figure 5.7. Aggregated flexibility energy-duration curves.

5.2.2 Electric water heater

Energy flexibility can be seen as an asset that can be utilised and restored. It is used during demand response activation and replenished during the subsequent rebound effect. Figure 4.1 illustrates different levels of flexibility activations. When flexibility is activated at maximum power (shown as a red line), it results in the most significant drop in demand. Still, this activation can only be sustained for a short duration. Conversely, a modest activation (shown as a purple line) has the opposite effect. This characteristic provides insight into how energy flexibility functions as an asset – the more it is used, the more quickly it is depleted. This thesis approaches the quantification of aggregated energy flexibility with a focus on mapping a curve showing the relationship between the power and duration of potential flexibility activations (shown as a blue line).

Energy flexibility on a device level can be evaluated by measuring the distance of the state variable (such as temperature or state of charge) from its boundaries. For instance, if the water temperature is 65 °C and consumers have set their comfort boundaries between 60 °C and 80 °C. Having a thermal model of the EWH would allow us to determine how long it can be turned on or off before reaching those boundaries. Figure 5.8 illustrates this concept in the example of an EWH.

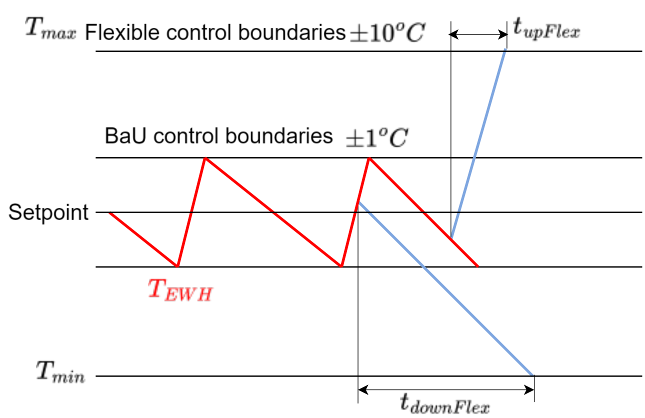

Figure 5.8. Illustration of EWH temperature trajectories with flexible activation.

A simulation was performed in MATLAB software to quantify the energy flexibility of 1000 EWHs and BESSs. In this simulation, the EWHs were either turned on or off, and the BESSs were set to charge or discharge with maximum power. This simulation was performed every minute of the day to determine the duration that each device can alter from its BaU behaviour. Based on this, the aggregated power/duration curves were created that describe the duration and the power that the BaU profile can be altered with flexibility activations.

The power and duration curves of aggregated EWHs are depicted in Figure 5.9 for both increasing and reducing the demand. These curves are presented as a surface to illustrate the fluctuations in energy flexibility throughout the day. The flexibility power/duration curve discussed in the previous section can be visualised as a segment of this surface at a specific time of the day. Examining the peak demand time in the morning (8 am), it is possible to see that the amount of flexible power available to increase the demand drops while simultaneously, the amount of flexible power to reduce the demand rises.

The following observations can be made about the aggregated energy flexibility of EWHs:

- The amount of energy flexibility available from EWHs is not consistent throughout the day. This is mainly because the hot water usage is also not consistent throughout the day.
- The energy flexibility provided by EWHs is very asymmetrical. There is much greater potential to increase the demand than to reduce it. This is because the coincidence factor of EWHs is typically very low since they are turned off most of the time.
- There is a significant difference in the duration that flexibility can be activated. The duration for which the demand can be increased is much less than it can be reduced. The demand can be increased for up to 1 hour and reduced for up to 8 hours. This large difference is seen because EWH units can be heated up rather quickly, while it takes much longer to cool down from either passive losses or hot water usage.

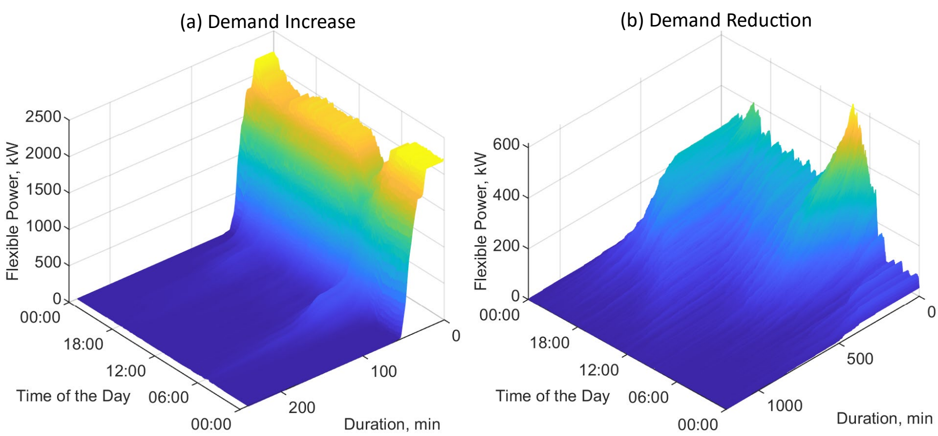

Figure 5.9. EWH aggregated energy flexibility curves for one day (a) Demand increase, (b) Demand reduction.

5.2.3 PV and battery system

The power and duration curves of aggregated BESSs are displayed in Figure 5.10 for both increasing and reducing demand. From these curves, we can make the following observations about the flexibility provided by residential small BESSs.

- Similar to EWH units, the flexibility provided by BESSs is not consistent throughout the day. This is because the SOC of batteries also varies throughout the day.
- There is an inverse relationship in the amount of available flexibility based on the direction it is provided. During the first half of the day, the BESSs provide more flexibility to increase the demand and no flexibility to reduce it. This is because up to noon, the BESSs are at the lower part of the SOC. However, an opposite phenomenon can be observed during the day as the on-site PV systems are charging the BESSs. In the afternoon, the SOC of BESSs starts increasing, which provides potential flexibility to reduce the demand by discharging the batteries.

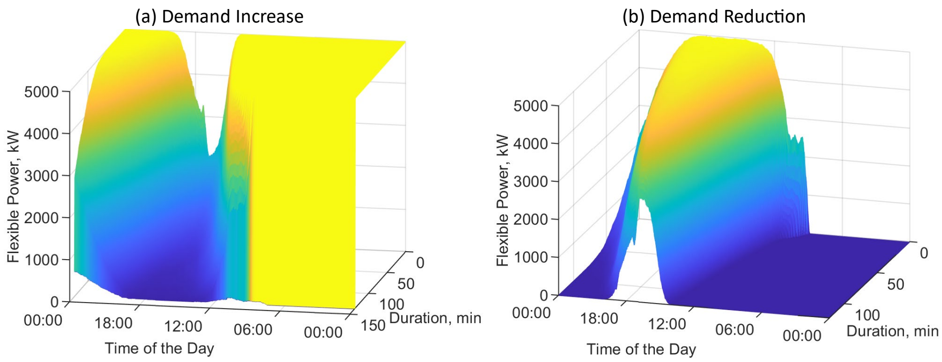

Figure 5.10. BESS aggregated energy flexibility curves for one day (a) Demand increase, (b) Demand reduction.

5.3 Rebound effect quantification

One crucial component of energy flexibility that needs to be taken into account is the rebound effect, which can affect grid balance and pose new difficulties. Figure 5.11 illustrates how this impact appears in the power profile following the flexibility activations of space heating. The simulation involves several independent flexibility activations of different durations (5, 15, 30, and 60 minutes). Subtracting the baseline power profile from the profile after flexibility is activated results in baseline-adjusted profiles, revealing the rebound effect.

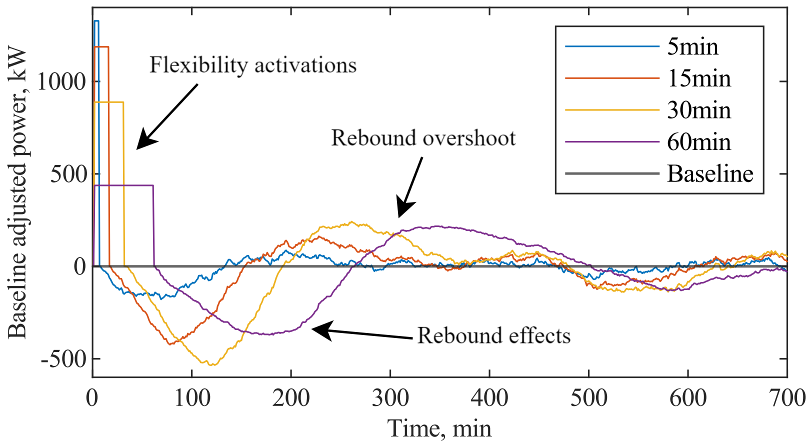

Figure 5.11. Baseline adjusted power profiles.

Simulations for flexibility activations up to 60 minutes in duration were run in order to have a better understanding of the rebound effect. The goal was to find out if the rebound effect is affected in any way by the magnitude of the flexibility activations. The duration, peak power, and energy characteristics were compared between the flexibility activations and the rebound effect, as seen in Figure 5.12. It is noteworthy that the rebound effect has an oscillatory behaviour, with an overshoot upon returning to the baseline. It is difficult to estimate the genuine rebound impact because of this phenomenon.

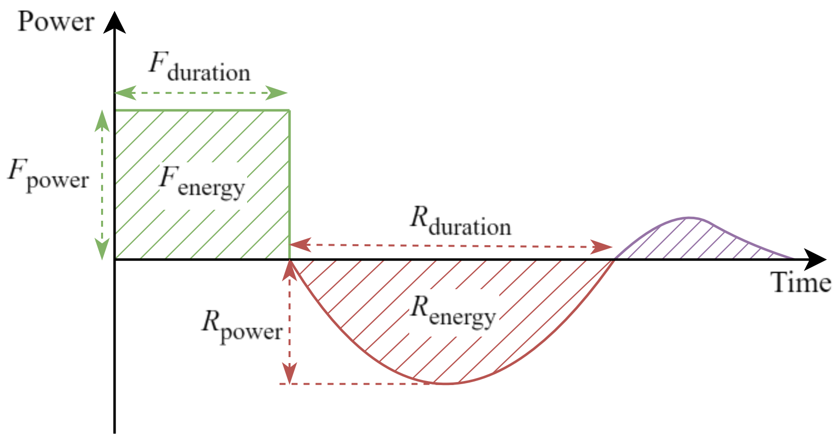

Figure 5.12. Flexibility activation characteristics.

Figure 5.13 displays the various properties of the rebound effect with respect to the duration of flexibility activation. Figure 5.14 displays the ratios of flexible power and energy to rebound power and energy. The following observations can be made regarding the peak power of the rebound effect:

- Increasing the demand using flexibility results in a significantly higher power rebound compared to reducing the demand. The highest power rebound occurs when the flexibility is activated for 20 to 40 minutes Figure 5.13.a).

- The longer the flexibility is activated, the closer the ratio of rebound power to activated flexibility power gets to 1 (Figure 5.14.a).
- When it comes to energy rebound, we can draw the following conclusions:
- Increasing demand results in a much higher energy rebound compared to reducing demand. The highest energy rebound occurs when flexibility is used for 30 to 60 minutes (Figure 5.13.b).
- The ratio of rebound energy to flexible energy levels off after activations longer than 10 minutes, reaching around 1.8 for demand increase and 1.5 for demand reduction. This means that for every unit of increased energy demand, 1.8 units are reduced later due to the rebound effect (Figure 5.14.b).

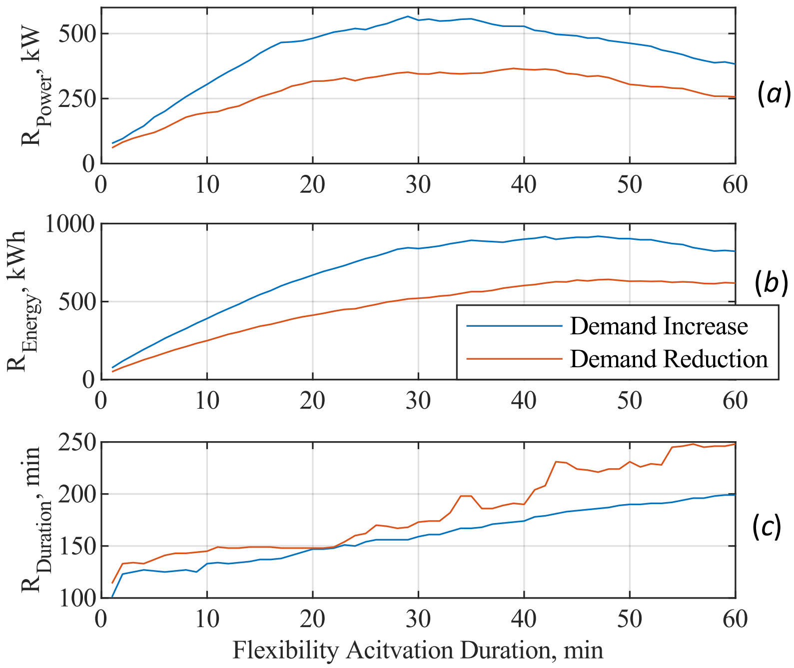

Figure 5.13. Rebound effect properties.

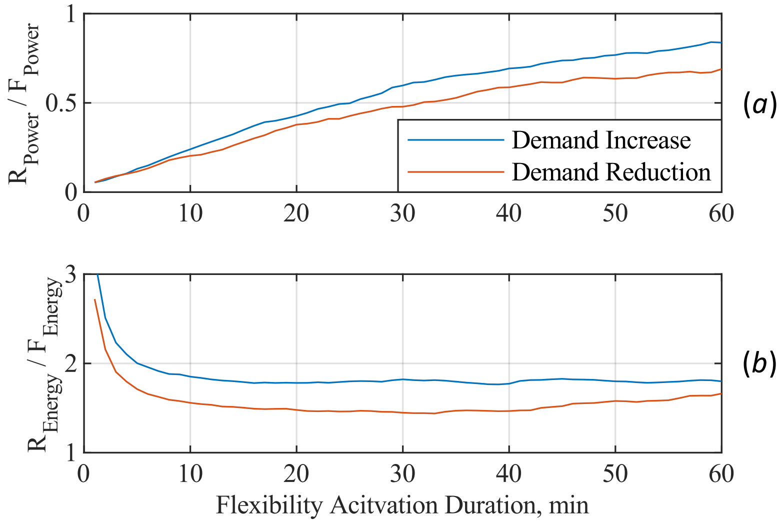

Figure 5.14. The power and energy ratios of flexibility and rebound.

In summary, an assessment of the rebound effect can be performed after energy flexibility. To quantify the rebound impact based on flexibility activations, the above numbers might be utilised as a guideline. For example, if an aggregator in reserve markets intends to utilise energy flexibility for 15 minutes, based on the flexibility quantification from Figure 5.6, there is a potential to increase demand power by a maximum of 1200 kW. The rebound effect of this activation would last approximately 130 minutes (Figure 5.13.c), with a peak power of 400 kW (Figure 5.13.a) and a total rebounded energy of around 500 kWh (Figure 5.13.b). It's important to note that these numbers are approximate and may vary based on portfolio size and seasonality. Nevertheless, they still illustrate the potential of the proposed quantification method.

In order to gain a better understanding of the oscillatory nature of the rebound effect, individual simulations were conducted for each weight class of buildings. The demand profiles with flexibility activations and without are shown in Figure 5.15 which illustrates the impact of rebound oscillations across different building types – light-weight, medium-weight, and heavy-weight. The findings reveal notable variations in the behaviour of flexibility recovery based on the thermal characteristics of each building type. Light-weight structures showed fast and short rebound oscillations, which is due to their lower thermal mass, which permits faster temperature adjustments but restricts long-lasting flexibility. Conversely, heavy-weight buildings exhibited slower and more extended rebound effects, marked by substantial power fluctuations, indicative of their greater thermal inertia.

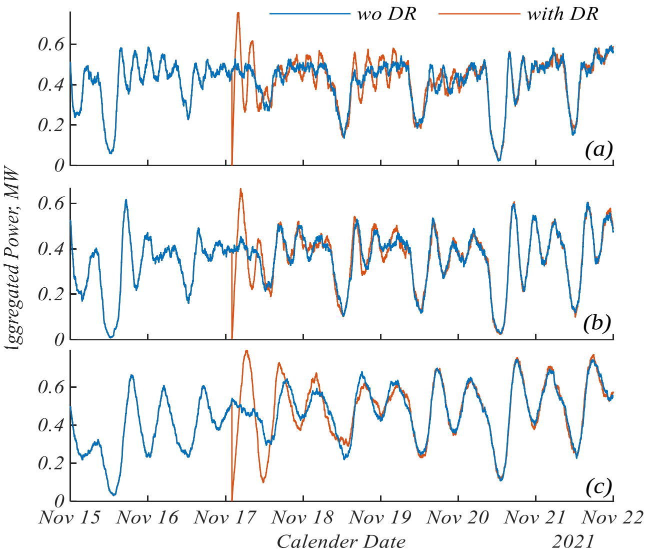

Figure 5.15. Aggregated power of different building types: (a) Light-weight, (b) Medium-weight, (c) Heavy-weight buildings [Paper III].

5.4 Conclusions

This chapter applied the developed power-duration curve method for quantifying energy flexibility through a simulation-based case study. The results demonstrated the method's effectiveness in characterising the flexibility potential of various residential energy systems, including space heating, electric water heaters, and battery storage systems.

The aggregated energy flexibility of 1000 heating systems, electric water heaters and battery energy storage systems was quantified through a simulation-based case study. The aggregated energy flexibility was assessed by mapping out the flexibility power-duration curves, which illustrate the potential aggregated power that flexible devices can activate with respect to the maximum duration the activation can be sustained.

The results revealed that both electric water heaters and battery systems exhibit inconsistent flexibility profiles throughout the day. Electric water heaters can offer significantly more flexibility to increase demand compared to reducing it, but the duration for increasing demand is shorter than for reducing it. Battery systems demonstrate an inverse relationship in their potential to increase or reduce demand. They provide greater flexibility to increase demand until noon, after which the potential to reduce demand becomes more dominant.

These findings highlight the proposed power-duration curve methods' ability to provide insights for grid operators and aggregators, enhancing their ability to integrate and manage flexible resources effectively by addressing the non-linear asymmetric behaviour of flexible resources.

6 Conclusions and future work

The main goal of this PhD research was to advance the understanding and practical application of energy flexibility within residential energy systems by developing an innovative approach for quantifying flexibility through power-duration curves.

A comprehensive literature review was performed that underscores the rising significance of energy flexibility as a fundamental aspect of modern energy systems, influenced by the increasing integration of variable renewable energy sources and the need for enhanced grid stability. The state-of-the-art analysis investigated the key aspects of energy flexibility, including its definitions, sources, methods of quantification, and associated challenges, while highlighting its importance in the shift toward sustainable and efficient energy systems. It was found that current methodologies frequently simplify the complex and dynamic characteristics of flexibility by depending on static or single-value measures, which emphasises the need for more sophisticated approaches, such as power-duration curves, that more accurately reflect the non-linear and time-varying behaviours of flexible loads.

The content section of the thesis focused on developing a new method for quantifying aggregated energy flexibility based on power-duration curves. The proposed method overcomes the drawbacks of current approaches by considering the non-linear, time-varying, and asymmetric characteristics of flexibility. By linking flexible power capacity with the duration of its activation, this method captures the dynamic interplay between these elements, making it applicable for both short-term and long-term flexibility applications. This broadens its usefulness for demand response programs, reserve markets, and balancing services, ensuring it can fulfil various operational and market requirements. The quantification method was explained in a detailed, step-by-step manner, and a simulation-based case study was carried out to demonstrate its application in quantifying aggregated energy flexibility.

One key finding of this research was the identification of inherent asymmetry in potential energy flexibility. The power capacity of flexibility was observed to vary considerably between increases and decreases in power, with the latter typically exhibiting less intense rebound effects. This asymmetry is vital for maintaining grid stability, as increases in power were found to generate more significant rebound oscillations, which could present challenges for operational planning. Additionally, the study showed that the connection between activation power and duration is fundamentally non-linear, challenging the assumption set by conventional linear models. This finding highlights the need for more advanced methodologies, such as the power-duration curve approach, to quantify and manage flexibility effectively.

The rebound effect emerged as another critical aspect of energy flexibility. The research showed that, in many cases, energy consumption during the recovery phase can offset or even exceed the energy savings achieved during activation. These effects were especially evident in systems with high thermal inertia, such as heavy-weight buildings, which displayed prolonged rebound oscillations. This behaviour highlights the necessity of factoring in rebound effects when designing and implementing demand-side management programs to ensure overall energy savings and maintain grid stability.

At the beginning of this thesis, four hypotheses were made. Based on the results, the following conclusions can be made:

- The first hypothesis, which proposed that quantifying energy flexibility using power-duration curves provides a more accurate and practical representation compared to single-value metrics, was confirmed. The power-duration curve method demonstrated its ability to capture the dynamic interplay between power and duration, providing valuable insights into both short-term and long-term flexibility potential.
- The second hypothesis, which stated that aggregated energy flexibility is inherently asymmetric and non-linear, was also confirmed by the research findings. The results showed significant differences in the capacity for increasing and decreasing power, emphasising the need for models that account for this asymmetry. Additionally, the relationship between activation power and duration was found to be non-linear, challenging the assumptions of traditional linear models.
- The third hypothesis, which stated that rebound effects in demand-side flexibility activation result in more energy being consumed during the recovery phase than saved during the flexibility activation, was partially validated. The research identified significant rebound effects, particularly in systems with high thermal inertia, where recovery energy often exceeded initial savings. However, the magnitude and impact of these effects varied depending on the type of system and operational scenario, suggesting that rebound effects are context-dependent and require careful consideration in flexibility management.
- Finally, the fourth hypothesis, which suggested that the asymmetry of energy flexibility impacts grid stability differently, with power increases showing more significant rebound effects, was confirmed. The findings demonstrated that power increases often led to more pronounced rebound oscillations, posing more significant challenges to grid stability compared to same magnitude power decreases. This highlights the importance of understanding and managing the asymmetric impacts of flexibility to ensure reliable grid operation.

6.1 Future work

The research conducted in this work can be expanded upon in future studies by researching and developing the following aspects:

- This thesis employed simplified heat pump models to demonstrate the quantification process of the developed method. To achieve a more precise evaluation of heat pump flexibility, more detailed models that consider the coefficient of performance (COP) variations with ambient temperature, along with various control strategies, such as partial load functioning and temperature setpoint management for flexible operations, should be considered.
- One potential direction is to apply the quantification approach developed in this thesis to other kinds of flexible devices, such as electric vehicles and shiftable appliances.

- An alternative avenue for research could focus on predicting flexibility. The method for quantifying flexibility developed in this thesis could be enhanced for forecasting by incorporating weather predictions and modelling temperature trends for the following day.
- The approach of the power-duration curve could be enhanced to incorporate techno-economic factors, including the expenses associated with activating flexibility, income from engaging in energy markets, and the operational costs of equipment. By including these elements, the method could deliver a more comprehensive assessment of flexibility, facilitating improved decision-making for aggregators and grid operators. This would enable stakeholders to maximise the technical capabilities and the economic feasibility of activating flexibility.
- Future research could focus on a more in-depth investigation of rebound effects that occur after the activation of flexibility. This involves measuring both the magnitude and duration of rebound energy use across various types of devices and operational situations. Gaining insights into the factors that affect rebound behaviour, such as the thermal inertia of devices, control methods, and user habits, would aid in the creation of mitigation strategies. Furthermore, studies could evaluate the cumulative effects of rebound phenomena on grid stability and energy market dynamics, providing valuable information for enhancing demand-side management initiatives.

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Abstract

Research and Development of Quantification Methods for Aggregated Energy Flexibility

The growing adoption of renewable energy sources has increased the need for flexibility on the demand side to maintain grid stability and efficient energy management. Nevertheless, current methods for quantifying flexibility often do not adequately capture the non-linearity, asymmetry, and rebound effects in flexible energy systems. This thesis introduces a novel method utilising power-duration curves to quantify aggregated energy flexibility within residential systems. The proposed approach offers a dynamic representation of flexibility over time, overcoming the drawbacks of traditional static and single-value methods.

The thesis starts with a comprehensive review of energy flexibility, its sources, and the challenges involved in its aggregation. Existing methods for quantifying flexibility are analysed. This evaluation emphasises the limitations of traditional methods, especially their shortcomings in capturing the non-linear and asymmetric characteristics of flexibility.

A novel power-duration curves method was developed to address these shortcomings. This approach defines flexibility by mapping power activation levels against the maximum sustainable activation duration, offering a more thorough and adaptable method. The process of applying the developed method is illustrated through simulation-based case studies that quantify the flexibility of residential heating systems, electric water heaters, and battery storage units. The findings suggest that the power-duration method offers a more accurate representation of flexibility, especially in capturing the asymmetry and non-linearity of flexibility.

A significant insight was gained in identifying rebound overshoot phenomena, where energy usage after activating flexibility displays oscillatory patterns, frequently surpassing initial consumption levels. This phenomenon carries substantial implications for demand-side management and grid stability, as improper flexibility activation may result in unintended variations in energy demand. The research also indicates that the asymmetry in energy flexibility significantly impacts grid stability, with power increases showing more substantial rebound effects compared to reductions.

The findings of this thesis contribute to the ongoing development of demand-side flexibility methods, delivering novel perspectives for energy aggregators, grid operators, and policymakers. By presenting a scalable and data-driven framework, the power-duration curve method improves the accuracy of flexibility quantifications and enables better integration of flexible resources into energy markets. Future research could focus on incorporating techno-economic factors into the model and further refining flexibility forecasting techniques.

Lühikokkuvõte

Agregeeritud energiapaindlikkuse kvantifitseerimismeetodi uurimine ja arendamine

Taastuvenergiaallikate üha laialdasem kasutuselevõtt on suurendanud vajadust tarbimispoolse paindlikkuse järele, et säilitada võrgu stabiilsus ja tagada tõhus energiakasutus. Siiski, olemasolevad paindlikkuse kvantifitseerimise meetodid ei suuda sageli piisavalt arvestada paindlike energiasüsteemide mittelineaarsuse, asümmeetria ja tagasilöögiefektiga. Käesolevas doktoritöös arendati välja uus meetod, mis kasutab võimsus-kestuse kõveraid, et kvantifitseerida elamupiirkondade agregeeritud energiapaindlikkust. Esitatud lähenemisviis pakub paindlikkuse dünaamilist kujutamist ajas, ületades traditsiooniliste staatiliste ja üksikväärtusel põhinevate meetodite puudusi.

Doktoritöö algab paindlikkuse allikate ja nende agregeerimise väljakutsete põhjaliku ülevaatega. Olemasolevad paindlikkuse kvantifitseerimise meetodite analüüs toob esile traditsiooniliste meetodite piirangud, eriti nende võimetuse kajastada paindlikkuse mittelineaarset ja asümmeetrilist olemust.

Selle puuduse ületamiseks töötati välja uus võimsus-kestuse kõveratel põhinev meetod, mis määratleb paindlikkuse kaardistades võimsuse aktiveerimise tasemed maksimaalse aktiveerimisaja suhtes, pakkudes seeläbi täpsemat kvantifitseerimismeetodit. Meetodi rakendamise protsessi illustreeritakse simulatsioonipõhiste uuringutega, kus kvantifitseeritakse elamute küttesüsteemide, elektriliste veeboilerite ja akusalvestusseadmete paindlikkust. Tulemused viitavad sellele, et võimsus-kestuse meetod võimaldab täpsemat paindlikkuse hinnangut, eriti paindlikkuse asümmeetria ja mittelineaarsuse kajastamisel.

Uuring tõi esile olulise nähtuse paindlikkuse tagasilöögiefektis, kus paindlikkuse aktiveerimisele järgnev energiatarbimine näitab võnkuvat mustrit, ületades sageli esialgse tarbimise taseme. See nähtus on oluline tarbimisjuhtimise ja võrgu stabiilsuse seisukohalt, kuna ebaõige paindlikkuse aktiveerimine võib põhjustada soovimatuid energiatarbimise kõikumisi. Lisaks viitavad uuringutulemused sellele, et paindlikkuse asümmeetria mõjutab võrgu stabiilsust, kusjuures võimsuse suurendamine põhjustab tugevamaid tagasilöögiefekte kui vähendamine.

Selle doktoritöö tulemused aitavad kaasa tarbimispoolse paindlikkuse kvantifitseerimise meetodite edasiarendamisele, pakkudes uusi perspektiive agregaatoritele, võrguoperaatoritele ja poliitikakujundajatele. Doktoritöös välja töötatud meetod võimaldab paremat paindlikkuse kvantifitseerimise täpsust ning soodustab paindlike ressursside paremat integreerimist energiaturgudele. Tuleviku-uuringud võiksid keskenduda tehnilis-majanduslike tegurite kaasamisele ja paindlikkuse prognoosimismeetodite täiustamisele.

Author’s Publications

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RESEARCH ARTICLE

Novel Quantification Method of Aggregated Energy Flexibility Based on Power-Duration Curves

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ABSTRACT Energy flexibility aggregation is an emerging concept regarded as a potential solution to the challenges of integrating distributed renewable energy sources. For aggregators to make informed decisions on how to utilise the energy flexibility of prosumers in their portfolios, it is crucial for them to use a suitable quantification method. This paper proposes a novel quantification method for aggregated energy flexibility based on flexibility curves created from the relationship between flexible power and its sustained duration. The proposed method also considers the asymmetric and non-linear properties of energy flexibility. The flexibility curves provide valuable insights for aggregators to make informed decisions on how to utilise their portfolios in a more optimal manner. We describe the quantification method with a step-by-step process. A simulation-based case study is conducted to illustrate the quantification process of residential heating systems. The aggregated flexibility curves and the rebound effects of 1000 different heat-pump-based buildings are constructed. The building's thermal behaviour is modelled using a resistive-capacitive model. We found that the power at which the flexibility can be activated highly depends on the activation duration. Additionally, the rebound effect can be quite substantial, with around 1.8 times the energy of the activation itself. We also noted an interesting phenomenon of rebound overshooting as the system oscillates to a stable position.

INDEX TERMS Aggregation, energy flexibility, heating system, rebound effect, quantification.

I. INTRODUCTION

There has been an increase in the use of Renewable Energy Sources (RES) due to growing concerns about global climate change. The proportion of RES in the European Union's (EU) power consumption has more than doubled from 16.9% in 2008 to 41.2% in 2022 [1]. Power networks are progressively integrating Variable Renewable Energy (VRE) sources such as wind and solar energy to accommodate this trend. However, VRE sources are subject to fluctuation and, therefore, require additional flexibility to balance the supply and demand of energy [2]. At present, the level of flexibility may not be sufficient to meet more than approximately 30% of the yearly demand through VREs [3]. There are two categories of energy flexibility sources: demand-side flexibility and supply-side flexibility [4]. Traditionally, the supply side has been responsible for balancing power by adjusting the output of power production units based on changes in demand. Incorporating generation units with different reaction times into the electricity grid allows for the creation of supply-side flexibility.

Demand-side flexibility refers to the ability to quickly adjust electrical loads in response to changes in supply or to smooth out long-term demand patterns. Examples of

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demand-side flexibility sources include the thermal mass of buildings, as well as flexible residential [5], commercial [6], and industrial [7] loads. These loads can be managed within users' comfort ranges. Residential loads that can be controlled include air conditioning, water heaters, refrigerators, dishwashers, washing machines, battery storage systems, and electric cars.

Evaluating the degree of flexibility of power systems can be a challenging task. Inflexibility indicators are usually more apparent [8], [9] and can include the following:

1) Inability to maintain a balance between supply and demand, leading to significant and repeated frequency excursions.
2) Substantial curtailment of RES due to transmission issues or excess traditional and inflexible electrical power.
3) Negative market pricing can indicate various inflexibilities, such as an abundance of renewable energy, a lack of demand, and constrained transmission infrastructure capacity.
4) Additional warning signs may include price volatility, high redispatch rates, area balancing violations, loss-of-load, and subsidised overcapacity.

Residential demand-side energy flexibility is a valuable asset that is currently not being fully utilised. Since individual household prosumers have limited capacity, they cannot contribute significantly to grid improvement and may find it challenging to participate in market activity [10]. Therefore, an aggregator should create a portfolio of several smaller controlled loads to form a more substantial entity. Aggregators act as intermediaries between end users and system operators, making contracts and participating in markets such as wholesale, reserve, and ancillary markets on behalf of prosumers [11].

Real-time aggregation processes and summarises data as it arrives, providing immediate insights and triggering quick actions. This enables real-time monitoring and control, for example in energy management systems [12]. On the other hand, predictive aggregation uses historical data to forecast future aggregated values, supporting strategic planning and resource optimisation by anticipating future conditions [13]. While real-time aggregation is crucial for operational decision-making with minimal delays, predictive aggregation focuses on long-term planning, allowing organisations to balance immediate responsiveness with proactive strategies.

Aggregators looking to participate in flexibility markets need to evaluate the available assets in their portfolio. This involves quantifying the total energy flexibility that can be aggregated. Since contracts for these markets are established before the actual delivery date, aggregators must estimate the amount of flexibility they can deliver and which flexibility requests to bid on. This requires forecasting the available flexibility in the future with a reasonable margin of uncertainty. However, factors like consumer behaviour, consumption habits, weather, and other variables can affect the availability of flexibility, making quantification and forecasting a challenging task [14].

Currently, there is no universally accepted definition for energy flexibility. Various researchers have attempted to define it according to their area of expertise. Some researchers consider a simple definition for flexibility as "*the ability to deviate from its reference electric load profile*" [15] or as "*the ability to reshape consumption patterns when interacting with the power grid*" [16]. Other more comprehensive definitions include: "*DSF can be defined as the ability to strategically alter electricity usage by consumers (either commercial or residential) from their normal consumption profiles, by responding to control signals from grid operators and/or financial incentives from electricity generators/aggregators. The scope of these signals is to modulate and optimise electricity usage and to balance electricity production and consumption*" [17]. An overview of the definitions of energy flexibility used by researchers in the literature has been compiled in the IEA EBC Annex 67 project "Energy Flexible Buildings" [18], based on which a general definition of energy flexibility was proposed: "*The energy flexibility of a building is the ability to manage its demand and generation according to local climate conditions, user needs, and grid requirements. Energy flexibility of buildings will thus allow for demand-side management/load control and thereby demand response based on the requirements of the surrounding grids*".

Activating energy flexibility is crucial for maintaining the stability and reliability of the grid. It allows for real-time adjustment of electricity supply and demand to prevent blackouts or grid failures [19]. Flexibility enables rapid changes in power consumption or generation, helping to keep grid frequency [20] and voltage levels stable, thus safeguarding infrastructure and service quality. This dynamic capability is especially valuable for handling unexpected changes in demand or disruptions like power plant outages or extreme weather events, which could otherwise threaten grid stability.

Furthermore, energy flexibility supports the integration of renewable energy sources, such as solar and wind, which are inherently variable and unpredictable. By allowing the energy system to adapt to fluctuations in renewable generation, flexibility makes it possible to maximise the use of clean energy and reduce dependence on fossil fuels. This minimises the curtailment of excess renewable energy, which might otherwise go unused during periods of low demand or insufficient storage capacity [21]. Ultimately, enhanced flexibility enables a more reliable, resilient, and sustainable energy grid that can effectively incorporate an increasing share of renewable power.

When traded on markets, energy flexibility is a valuable asset that can be used to provide services for grid enhancements. Therefore, for practical purposes, it is crucial to quantify energy flexibility meaningfully and quantitatively. Various types of quantification methods are discussed in the existing literature. In [22], six different quantification methods were reviewed and evaluated using a simulation case study based on thermal storages. A review of energy flexibility key performance indicators related to load matching and grid interactions is given in [23]. Other flexibility metrics such as peak power reduction, flexibility factor, self-sufficiency, and capacity of active demand response are discussed in [24].

Depending on the source of flexibility, these quantification methods rely on data related to building characteristics, weather, indoor environment, building automation systems, power and energy metering, and occupancy usage. The accessibility of how difficult it is to obtain this data is discussed in [25].

A short overview of energy flexibility quantification methods and frameworks is presented in TABLE 1. The analysis includes the parameters, metrics, and indices quantifying flexibility. The quantification methods can be broadly categorised based on whether the flexibility was evaluated as a singular value, or as a curve or a region that maps out the relationship between two or more values, and if the symmetry or linearity is considered. It was found that if flexibility is evaluated using a single number, then it is typically quantified in relation to flexible power [26] or energy values [17], [27], or temporal aspects such as the length of time consumption can be shifted [28] or in a more abstract manner using flexibility indices that for example describe flexibility's potential for load covering, shifting and scheduling [16]. If instead a curve is used, then a relationship between two parameters is established, for example the flexible energy and the cost of activation [15]. More complex methods quantify flexibility as a region or a domain of feasible operations under the considerations of network constraints, ramp rate, etc [29].

Another important aspect is whether the quantification method considers flexibility as an asymmetrical and non-linear resource. The term "asymmetry" refers to the difference in the amount of flexibility to either increase or decrease demand. The coincidence factor is a significant factor for loads in this context. For instance, electric water heaters have a low coincidence factor, meaning that only a small fraction of them are turned on at any given time. Therefore, there are many more water heaters that could be turned on to increase the demand, as opposed to a few devices that can be turned off to reduce the demand. The same applies to battery systems, as they are not always at 50% state-of-charge to provide equal amounts of up- and downregulation. Thus, when quantifying the flexibility of the entire portfolio, it becomes clear that there are unequal levels of flexibility to increase or decrease the demand. It is important for quantification methods to consider the asymmetry of flexibility since some markets require symmetrical bids, while flexibility sources are not always symmetrical.

Linearity describes whether there is a linear relationship between two or more parameters; for example, the power and the duration the flexibility can be activated. It is important to consider the non-linearity of flexibility to provide a realistic flexibility estimate, as there can be a non-linear relationship between power and duration, power and cost aspects, etc. The flexibility envelope method presented in [30] considers the asymmetry by providing the envelopes for both up and down-regulation. The cost curves method of [15] considers both asymmetry and non-linearity by quantifying flexibility as the relationship between potential flexible energy and the cost associated as a curve for both demand increase and reduction.

Based on the literature review, there is a lack of quantification methods that consider the asymmetry and non-linearity of energy flexibility. Therefore, this paper proposes a new quantification method that evaluates the relationship of flexible power and energy with the duration that it can be activated while considering the asymmetry of non-linearity. The novelties presented in this paper are as follows:

1) A method for quantifying the connection between the flexible power and energy with the duration of activation.
2) The proposed method considers the properties of asymmetry and non-linearity of aggregated energy flexibility.

The paper is structured as follows: Section II provides an overview of the proposed quantification method. Section III describes modelling and simulation of buildings and their heating system. Section IV presents a case study to illustrate the proposed quantification method. Section V delves into a discussion related to the findings and future work. Finally, Section VI concludes the paper.

II. PROPOSED QUANTIFICATION METHOD

A. FLEXIBILITY POWER DURATION CURVES

Energy flexibility can be thought of as an asset that can be spent and regenerated. It is spent when it is activated with demand response and regenerates during the subsequent rebound effect. Fig. 1 illustrates different intensity levels of flexibility activations and their rebound effects for thermostatically controlled loads, such as heating systems. Note that not all types of flexibility need to be regenerated immediately, for example BESS and EV-charging. When flexibility is activated with maximum power (shown as a red line), it results in the most significant drop in demand, but this activation can only be sustained for a short duration. However, the opposite effect is observed when a modest activation is performed (shown as a purple line). This characteristic provides insight into how energy flexibility works as an asset - the more it is used, the more quickly it is depleted.

To quantify aggregated energy flexibility, a novel approach is proposed in this paper. The approach focuses on mapping a curve that shows the connection between the power and duration of possible flexibility activations (shown as a blue line). Utilising this quantification method would provide aggregators with a more detailed overview of their energy flexibility assets. Aggregators can engage in various energy markets, each with its own specifications for the amount of electricity to be provided and the delivery duration. For instance, in reserve markets, aggregators would need to activate their

TABLE 1. Overview of quantification methods for energy flexibility.

Ref.	Short description	Case study	Quantification parameters, metrics, indices	Flexibility quantified using a single value, curve, or a region	Considers asymmetry, non-linearity
[17]	A unified framework is proposed for capturing the DR potential of thermal and electrical systems.	One building with heat pump, PV system, EV, and BESS	Indices of self-consumption, storage capacity, storage efficiency	Single value	Asymmetry
[16]	A quantification methodology for five energy flexibility indices is proposed.	Office building with HVAC, dimmable lighting, EV charging	Indices related to load covering, shifting, scheduling, moderate regulation, and fast regulation	Single value	No
[31]	A methodology that models flexible resources as a virtual energy storage system	Office and apartment building ventilation systems	Power and energy capacity, State of Charge, self-discharge rate	Single value	No
[27]	The proposed model schedules a set of appliances and calculates the aggregated flexibility according to the energy and flexibility prices	Aggregated HVACs, pool pumps, electric water heaters	Flexible power	Single value	No
[15]	A methodology for computing the flexibility of buildings using cost curves	Office building HVAC	Flexible energy and its related cost	Curve	Asymmetry and non-linearity
[29]	A framework to model and characterise DER flexibility using the concept of nodal operating envelope under network constraints, ramping rate, cost, etc.	Distributed network consisting of a BESS, load, and a generator	PQ chart of a flexible operating region	Region	Asymmetry and non-linearity
[30]	A methodology based on determining the flexibility envelopes of two boundaries conditions when loads are activated either as early or as late in the day as possible.	Wet appliances, domestic hot water buffers and EVs	Flexible power and energy	Region	Asymmetry
This paper	The proposed method quantifies energy flexibility as a power-duration curve	Aggregated residential heat pumps	Flexible power and energy, duration of activation	Curve	Asymmetry and non-linearity

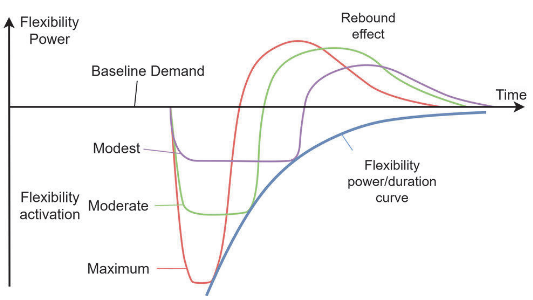

FIGURE 1. Illustration of flexibility activations at different power levels.

flexibility for a short period (up to 15 minutes), while for day-ahead wholesale markets, activations can last for several hours. It is apparent that the aggregator would be unable to sustain the same high power reserve market flexibility activation for long-duration wholesale market activation. Thus, the method of quantification proposed in this paper provides aggregators with a greater insight into their flexibility assets, enabling for a more informed decision-making.

B. QUANTIFICATION METHOD

Fig. 2 provides an overview of the proposed quantification method. In the first step, the quantification method starts with data processing. This includes the acquisition, cleaning, and filtering of the data. The relevant data needed for quantification consists of measurement or device specification data that influences the usage of flexible devices. When it comes to space heating, meteorological data such as weather forecasts of outdoor ambient temperature and solar irradiance affect the demand for heating energy. For other flexible devices, such as domestic hot water (DHW) units, the hot water usage profile would need to be acquired.

In the second step, it is essential to select an appropriate model for each type of device and to determine its parameters. The modelling of the behaviour of devices is crucial to ensure that the appliances remain within the comfort boundaries established by the consumers when the flexibility is activated. Thermostatically controlled loads (TCLs), such as the heating system of a building or a DHW unit, can be modelled using a thermal resistive-capacitive model.

In the third step, the business-as-usual (BaU) operation case of appliances should be modelled to determine the electrical demand profile under normal operation without flexible activation. This step can be considered as baseline estimation part of the quantification process.

In the fourth step, the potential flexibility can be quantified based on the demand profiles determined in the previous step, the models of flexible devices, and the state of each flexible device within their comfort ranges. This involves simulating flexibility activations of devices at each time step, meaning the on/off turning of devices until the comfort boundaries are reached.

In the last, fifth step, the power-duration curves can be constructed by knowing the power of the devices and the duration that the flexibility can be activated.

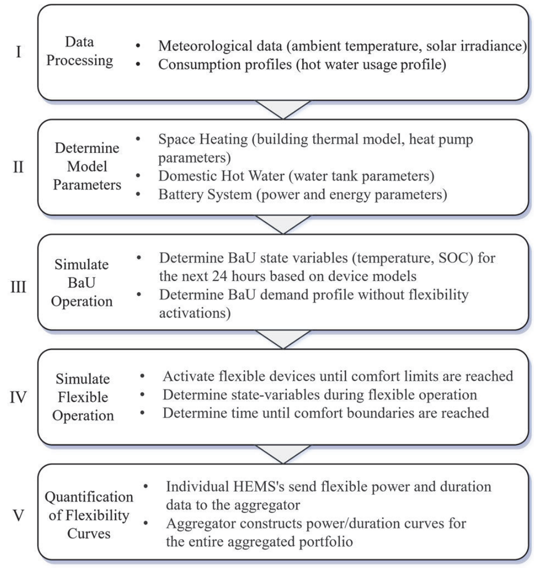

FIGURE 2. The quantification process of the proposed method.

C. AGGREGATION FRAMEWORK

In order to demonstrate the advantages of the proposed method of quantification, a simulation-based case study was conducted, which aimed to quantify the aggregated energy flexibility of 1000 different buildings that use heat-pump based space heating.

The Aggregation framework shown in Fig. 3 can be used for real-world implementation. However, some simplifications have been made for the simulation-based case study. The framework consists of two main components: the aggregator and the Home Energy Management Systems (HEMS) of each building. HEMS receives inputs from weather forecasts, heat pumps, and homeowners (step 1 of the quantification). While the ambient temperature T_a and solar irradiance (GHI) would be received from outside cloud servers, we have used data from PVGIS for simulation purposes Through a datalink with the heat pump, HEMS receives the indoor temperature T_{in} and electricity consumption P_{el}. Homeowners can input their comfort requirements by setting upper T_{max} and lower T_{min} limits for the indoor temperature.

The purpose of the HEMS is to perform three main operations: thermal model identification, Business-as-Usual simulation, and flexible operation simulation. Thermal model identification is necessary since, in a real-world implementation, the RC thermal model would need to be trained for each building (step 2 of the quantification).

However, for simulation purposes, the RC parameters were sampled from publications and guidelines, this process will be discussed in section III.

Based on the identified thermal model, the weather forecasts, heat pump telemetry, and the homeowners' comfort requirements, a BaU simulation is conducted to model the baseline behaviour without any flexibility activations (step 3 of the quantification). After establishing the baseline, a simulation is conducted to determine the duration that the heating system can either be turned on t_{upFlex} or off $t_{downFlex}$ (step 4 of the quantification). These durations are then communicated to the aggregator alongside the baseline power profile P_{BaU}. This data allows the aggregator to map the flexibility curves (step 5 of the quantification).

III. MODELLING AND SIMULATION OF SPACE HEATING

To accurately quantify the energy flexibility of a heating system, it is necessary to model the thermal behaviour of the building. This is because the indoor temperature must always be kept within the comfort range of the occupants, so the building's thermal insulation and thermal mass must be taken into account. As a result, the kWh/°C relationship can vary from building to building, meaning that some buildings require more energy for heating, while others can go for more extended periods with the heating turned off.

A Resistive-Capacitive RC model was used to model buildings' thermal behaviour. In contrast to white-box models, which integrate more detailed characteristics, an RC model is a grey-box model that roughly incorporates building parameters related to their thermal dynamics. Similar to electrical circuits with resistors and capacitors, thermal RC models include the thermal capacitances and resistances (U-values) of various building components.

This study used a 3R2C thermal model consisting of three thermal resistors and two thermal capacitors [32]. The model considers the building envelope (external walls), the windows, and the internal thermal mass (interior walls, furniture,

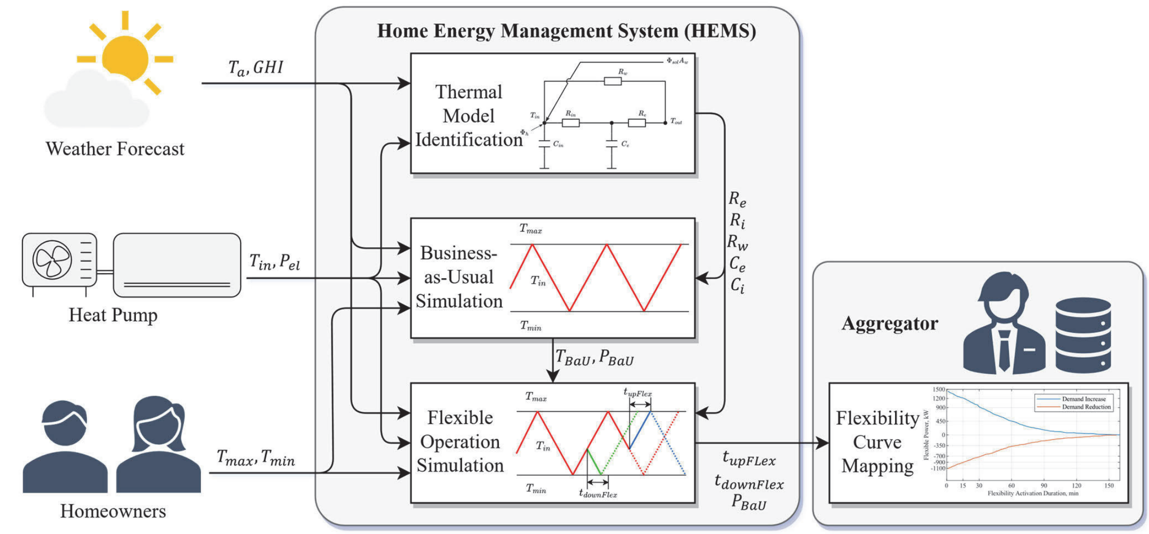

FIGURE 3. Overview of the energy flexibility quantification framework.

and air) as the three primary components of a building. Fig. 4 displays a simplified thermal network design applied in this work. It can be observed that the outdoor temperature T_{out} influences the indoor temperature T_{in} through both the building envelope and the windows. The solar effect is assumed to transmit only through the windows. The study assumes that the indoor temperature is uniform throughout the building. TABLE 2 describes the thermal RC model's inputs, outputs, and parameters.

The generic heat-balance equation (1) can be used to create a first-order differential equation for each node n in a thermal system with N elements:

$$C_n \frac{dT_n}{dt} = \sum_{i \in N} \frac{T_i - T_n}{R_i} \Phi_n \tag{1}$$

where C_n and T_n represent the thermal capacitance and the temperature of node n, respectively, R_i represents the thermal resistance between two connected nodes i and n, and Φ_n represents the total heat fluxes applied to node n [33].

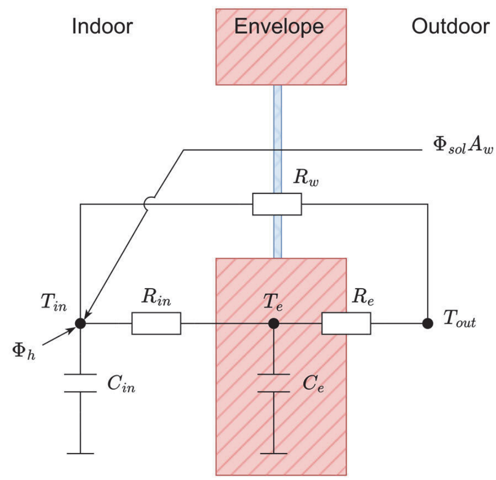

FIGURE 4. RC thermal networks of a building, adapted from [32].

TABLE 2. Description of thermal network parameters.

	Symbol	Description
Inputs	T_{out}	Ambient temperature, °C
	ϕ_{sol}	Global horizontal solar irradiance, W/m^2
	ϕ_h	Heating power, W
Outputs	T_{in}	Indoor air temperature, °C
	T_e	Envelope temperature, °C
Parameters	R_e	Envelope thermal resistance, °C/W
	C_e	Envelope thermal capacitance, J/°C
	R_{in}	Inner mass thermal resistance, °C/W
	C_{in}	Inner mass thermal capacitance, J/°C
	R_w	Window thermal resistance, °C/W

The equation (1) shows that the complexity of a thermal RC model may vary depending on the number of components considered. A more detailed model may be achieved by integrating features from several architectural elements, such as the construction and insulation layers of outside and interior walls, the roof, and other building components. RC thermal networks are, thus, essentially models that may be made up of various combinations of resistors and capacitors representing parts of buildings.

The heat-balance equation (1) can be applied to the thermal RC network topology in Fig. 4 to derive the differential

TABLE 3. Typical thermal network parameters for different types of residential buildings.

Envelope Thermal Network Parameters [34]		
Class	$R_e\left(\frac{\mathrm{m^2C}}{\mathrm{W}}/\mathrm{m}^2\right)$	$C_e\left(\frac{kJ}{\mathrm{m^2C}}\cdot \mathrm{m}^2\right)$
Light-Weight	$3.1498/A_e$	$76.852 \cdot A_e$
Medium-Weight	$3.8238/A_e$	$183.724 \cdot A_e$
Heavy-Weight	$2.1917/A_e$	$402.102 \cdot A_e$
Windows	$0.8333/A_w$	0
Inner Mass Thermal Network Parameters [35]		
Class	$R_i\left(\frac{\mathrm{m^2C}}{\mathrm{W}}/\mathrm{m}^2\right)$	$C_i\left(\frac{kJ}{\mathrm{m^2C}}\cdot \mathrm{m}^2\right)$
Light-Weight	$0.13/A_{fl}$	$110 \cdot A_{fl}$
Medium-Weight	$0.13/A_{fl}$	$165 \cdot A_{fl}$
Heavy-Weight	$0.13/A_{fl}$	$260 \cdot A_{fl}$
Building Size Parameters		
Floor Area, A_{fl}	$uniform(50, 200)$, m^2	
Building Height	$uniform(5, 12)$, m	
Window-to-Wall Ratio	$uniform(20, 50)$, %	

equations that describe the temperature of the inner mass (2) and the envelope (3) of a building.

$$\dot{T}_{in} = \frac{1}{R_{in}C_{in}}T_e - \left(\frac{1}{R_{in}C_{in}} + \frac{1}{R_wC_{in}}\right)T_{in} + \frac{1}{R_wC_{in}}T_{out} + \frac{1}{C_{in}}\phi_h + \frac{1}{C_{in}}\phi_{sol}A_w \tag{2}$$

$$\dot{T}_e = -\left(\frac{1}{R_{in}C_e} + \frac{1}{R_eC_e}\right)T_e - \frac{1}{R_{in}C_e}T_{in} + \frac{1}{R_eC_e}T_{out} \tag{3}$$

It is possible to model the thermal behaviour of a building for each timestep by converting the above differential equations into difference equations (4) and (5).

$$T_i(t+1) = T_i(t) + \left(\frac{T_e(t) - T_i(t)}{R_iC_i} + \frac{T_a(t) - T_i(t)}{R_wC_i} + \frac{\Phi_{sol}(t)A_w}{C_i} + \frac{\Phi_h(t)}{C_i}\right)\Delta t \tag{4}$$

$$T_e(t+1) = T_e(t) + \left(\frac{T_i(t) - T_e(t)}{R_iC_e} + \frac{T_a(t) - T_e(t)}{R_eC_e}\right)\Delta t \tag{5}$$

The thermal behaviour of buildings is influenced by various factors such as size, insulation level, construction materials, window-to-wall ratio, number of inner walls, and others. These factors may differ from one building to another, so when studying the aggregated energy flexibility of multiple buildings, it's crucial to simulate various types of buildings. However, estimating the parameters of an RC model for a specific building is a complicated process. To the best of the author's knowledge, no publicly available database includes the number of actual building thermal network parameters required for simulating aggregated control.

Therefore, in this work, we need to generate parameters based on existing guidelines. From TABLE 2, it is clear that we need to generate six different parameters for each building to model its thermal behaviour. Typical thermal network values for residential buildings are shown in TABLE 3 based on weight class. The ranges of values for typical building envelopes were determined in [34] based on a first-principles analysis of different building construction materials. The standard ISO 52016-1:2017 [35] provides typical values for the inner thermal mass of buildings.

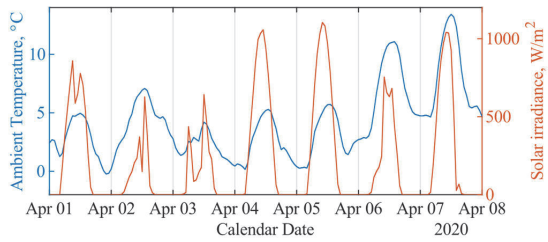

FIGURE 5. Meteorological data obtained from PVGIS [36].

The weight class of a building refers to its construction materials. For instance, the exterior walls of light-weight buildings comprise stucco, insulation, and plaster/gypsum. Medium-weight buildings use brick, air space, insulation, and gypsum, while heavy-weight buildings use brick, heavy-weight concrete, insulation, and gypsum. We assumed that the thermal resistance of windows is that of typical double-glazed windows, while the thermal capacitance of windows is negligible.

IV. CASE STUDY

A. FLEXIBILITY QUANTIFICATION

In this subsection, we will demonstrate an example of how to quantify aggregated energy flexibility for space heating using the proposed method shown in Fig. 2. The modelling and simulations were carried out using the MatLab software.

The quantification process begins by importing the relevant data for space heating, specifically the meteorological data. For this simulation, we used meteorological data from the beginning of April 2020 obtained from PVGIS [36]. We chose this date because it reflects both the cold outdoor temperature and solar heating factors that affect space heating usage, as depicted in Fig. 5.

The next step in the quantification method involves modelling the thermal dynamics of buildings. In this paper, a simple 3R2C thermal network was used. However, for higher accuracy, this model can be made more complex by incorporating additional resistors and capacitors. From TABLE 3, it can be observed that all thermal network parameters are proportional to either the floor area capacity A_{fl}, the exterior wall area capacity A_e, or the window area capacity A_w. This means that many different building thermal network parameters can be generated by sampling typical values for building constructional parameters [37], [38]. Different-sized buildings, with floor areas ranging from 50 to 200 square meters, building heights of 5 to 12 meters, and window-to-wall ratios of 20 to 50%, were sampled from a uniform

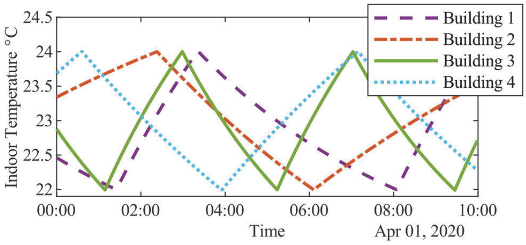

FIGURE 6. Examples of 4 simulated building temperature trajectories.

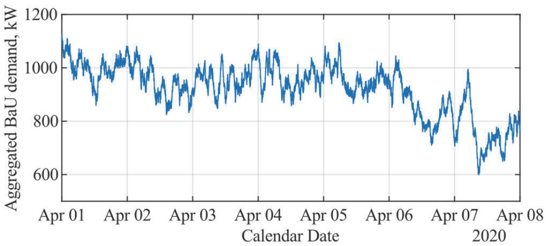

FIGURE 7. Aggregated demand of 1000 simulated buildings for BaU case.

distribution. Based on the floor area capacity A_{fl} and the building height, the area of the exterior envelope A_e was calculated. Using the generated window-to-wall ratio, the area of the windows capacity A_e can be derived. By generating different types of buildings, it is possible to simulate an aggregator's portfolio that includes many different kinds of buildings with respect to their thermal characteristics.

The initialization values for the heating system's on/off status, the temperature of the indoor area and the envelope were determined by performing a preliminary BaU simulation. This was necessary to reduce the transients at the beginning of the simulation that occur from random initialization of state parameters. The preliminary simulation was initialized by sampling the indoor and envelope temperatures from a uniform distribution between 22 and 24 degrees Celsius and the heating system on/off state from integer sampling between 0 and 1. The output of the preliminary simulation was then used to initialize the flexibility quantification simulations. In a real-world case, this step would not be needed as the indoor temperature and the state of the heating system would already be known. The thermal heating power was assumed to be proportional to the floor area of the building between 6 kW and 12 kW. The COP of the heat pump was assumed to be between 3 and 4 to account for devices from different manufacturers.

The third step in quantification involves simulating the Business-as-Usual (BaU) scenario, which is necessary to determine the baseline demand without any flexibility activations. The BaU scenario can be simulated using the RC-thermal network models created in the previous step. By knowing the starting indoor temperature and the effects

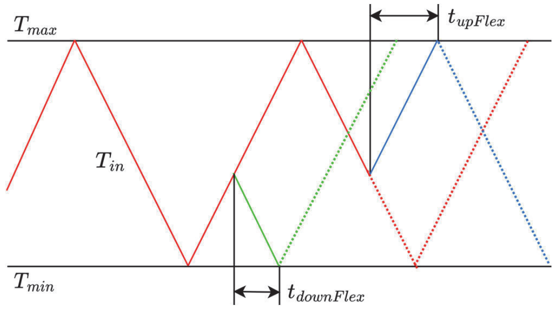

FIGURE 8. Illustration of temperature trajectories with flexible activation.

of external factors such as outdoor ambient temperature and solar effects, we can model the temperature trajectories using equations (4) and (5). In the BaU scenario, it is assumed that the setpoint for indoor temperature is 23 °C and the deadband of the on/off control is $\pm 1°C$. Fig. 6 provides an example of 4 different building temperature trajectories, showing that different buildings take varying amounts of time to heat up and cool down. Fig. 7 shows the demand profile for the BaU case. Comparing it to the ambient temperature graph in Fig. 5, we can notice that during the first five days of the week, when the temperature is between +1 °C and +5 °C, the demand for 1000 heat pump units is between 850 kW and 1100 kW. Towards the end of the week, when the temperature increases, we see a reduction in the electricity demand.

Once we have determined the demand profile and on-off switching of the heat pumps during the BaU case, we can simulate flexible operation. The flexibility provision is assumed to take place in the same temperature range as the BaU scenario (22 – 24°C). Let's say the room temperature of a building is 22.5°C, and the heat pump is in the off state; then, by turning it on we can increase the temperature up to 24°C. If a homeowner is willing to go beyond the BaU range and provide more flexibility (up to 25°C), then the duration aspect of the house's flexibility would increase. The flexibility in heating systems depends on the owners' comfort requirements and their willingness to deviate from them. For this paper, we have assumed a strict requirement of a maximum ± 1°C deviation from the setpoint. The flexibility can be quantified by determining the distance of the current indoor temperature from the upper and lower boundaries. Using this information, we can predict how long we can turn the heating on or off. Fig. 8 provides an illustration of this. We can observe that the amount of energy flexibility available in each building varies, depending on the proximity of the indoor temperature to the temperature boundaries at any given time. If the indoor temperature is close to the upper boundary, there is very little flexibility to increase the demand as the heating can only be turned on for a short period. Conversely, there is more flexibility to turn off the heating. The opposite is true if the indoor temperature is close to the lower boundary.

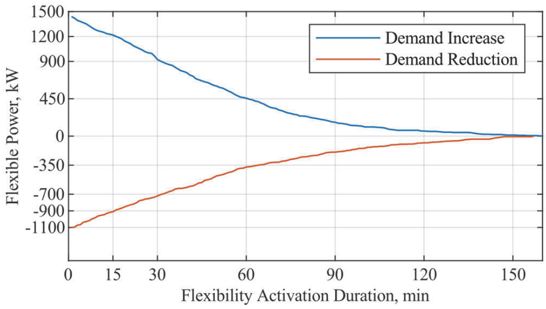

FIGURE 9. Aggregated flexibility power-duration curves.

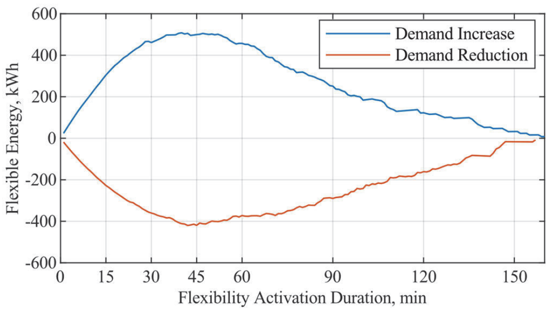

FIGURE 10. Aggregated flexibility energy-duration curves.

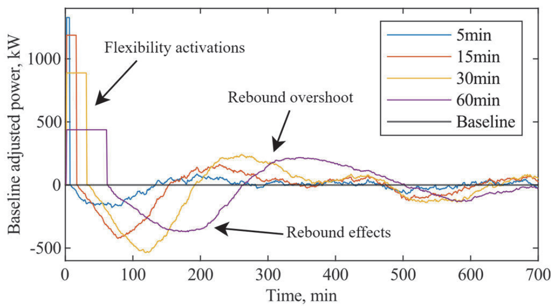

FIGURE 11. Baseline adjusted power profiles.

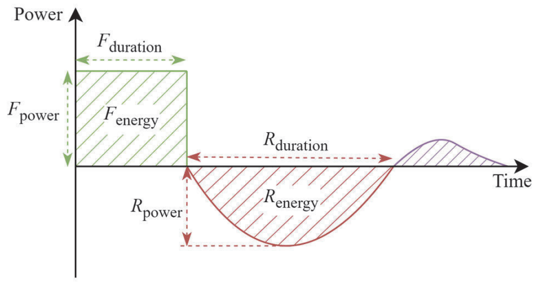

FIGURE 12. Flexibility activation characteristics.

During the final step of the quantification process, all the buildings involved in the process provide the required data to the aggregator for quantification of aggregated energy flexibility. The data consists of the on-off status of the heat pumps and the time durations for which heating can either be turned on or off until the temperature comfort boundaries are reached. Based on this information, the aggregator can plot two curves that show the potential flexibility to increase or decrease the demand, as depicted in Fig. 9. This approach ensures a higher level of privacy since the demand profiles, indoor temperatures, and boundary levels themselves are not shared with the aggregator.

By using the proposed quantification method, aggregators can gain important insights into the energy flexibility of their portfolios and can help them make more informed decisions on how to use their flexibility. For instance, if an aggregator's business plan is focused on reserve markets, they might be interested in activations with durations of up to 15 minutes. Fig. 9 shows that there is potential aggregated energy flexibility to increase or reduce demand by 1,200 kW and 900 kW respectively. On the other hand, if an aggregator is instead focused on day-ahead markets and wants to provide flexibility for 60 minutes, they will notice that using the same portfolio of 1000 heat pumps, the potential aggregated energy flexibility to increase or reduce the demand has now dropped to 450 kW and 350 kW, respectively. It is possible to deduce from these flexibility curves that the amount of flexible power not only reduces with longer activation but is also unsymmetrical. This is relevant because some markets require symmetrical bids. Additionally, the flexible power can be plotted in the context of flexible energy, as shown in Fig. 10. Here, it is possible to see how much flexible energy is available to increase or decrease consumption based on the activation duration.

B. REBOUND QUANTIFICAITON

Energy flexibility has an important aspect called the rebound effect that must be considered, as it can impact the grid balance and create new challenges. This effect can be seen in the power profile after the flexibility activation, as shown in Fig. 11. The simulation includes multiple independent flexibility activations of different durations (5, 15, 30, and 60 minutes). By subtracting the baseline power profile from the profile after flexibility is activated, we obtain baseline-adjusted profiles. After the flexibility activation, a rebound effect is observed.

To gain a better understanding of the rebound effect, simulations were conducted for flexibility activations lasting up to 60 minutes. The aim was to investigate whether the magnitude of the flexibility activations has any impact on the rebound effect. The properties of duration, peak power, and energy, as shown in Fig. 12, were compared between the flexibility activations and the rebound effect. It's worth noting that the rebound effect appears to have an oscillating behaviour,

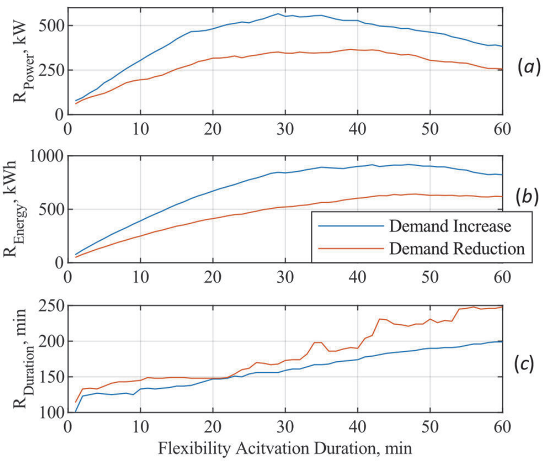

FIGURE 13. Rebound effect properties.

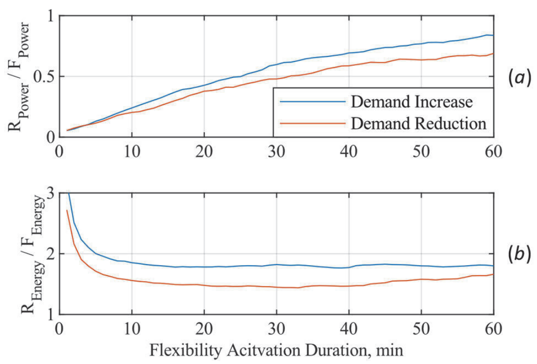

FIGURE 14. The power and energy ratios of flexibility and rebound.

overshooting as it returns to the baseline. This phenomenon makes quantifying the true rebound effect challenging.

The results for the rebound effect related to different durations of flexibility activation are displayed in Fig. 13, and the ratios of rebound power and energy compared to flexible power and energy are shown in Fig. 14. The following observations can be made regarding the peak power of the rebound effect:

1) Increasing the demand using flexibility leads to a significantly higher power rebound compared to reducing the demand. The highest power rebound happens when the flexibility is activated for 20 to 40 minutes (Fig. 13.a).
2) The longer the flexibility is activated, the closer the ratio of rebound power to activated flexibility power gets to 1 (Fig. 14.a).
3) In terms of energy rebound, the following conclusions can be made:
4) Increasing the demand leads to a substantially higher energy rebound compared to reducing the demand. The highest amount of energy rebound occurs when flexibility is activated for 30 to 60 minutes (Fig. 13.b).
5) The ratio of rebound energy to flexible energy reaches a plateau after activations longer than 10 minutes, at around 1.8 and 1.5 for demand increase and reduction, respectively. This means that for every unit of increased energy demand, 1.8 units of are reduced due to the rebound effect (Fig. 14.b).

To summarise, the rebound effect can be quantified after energy flexibility. The figures provided can be used as guidelines to quantify the rebound effect based on flexibility activations. For instance, if an aggregator operating on reserve markets wants to dispatch energy flexibility for 15 minutes, based on the flexibility quantification from Fig. 9, there is potential to increase the demand power by a maximum of 1200 kW. The rebound effect associated with this activation would last around 130 minutes (Fig. 13.c), have a peak power of 400 kW (Fig. 13.a), and a total rebounded energy of around 500 kWh (Fig. 13.b). Note that these figures are indicative and subject to change based on portfolio size and seasonality. Nonetheless, they still demonstrate the potential of the proposed quantification method.

V. DISCUSSION AND FUTURE DIRECTIONS

In this study, a new method was developed to quantify the aggregated energy flexibility and the subsequent rebound effect. This method provides valuable insights into the potential of energy flexibility as an asset that aggregators can use to make informed decisions on how to use it. However, it is important to note that the flexibility curves shown in this paper's case study are only indicative. The curves may change depending on the ambient temperature and seasons. The crucial conclusion to draw is that the potential amount of flexibility a system has is highly dependent on the duration the flexibility is activated. Therefore, it may not be appropriate to quantify the total energy flexibility of a system using a singular power or energy value.

For the case study simulation performed in this paper, all the model parameters were chosen from practical guidelines to represent a diverse range of aggregated buildings. However, in order to use the RC model and the quantification method developed in this paper for real-world applications, the parameters would have to be determined for each building. One way to achieve this is by using an opposite approach where the inputs and outputs of the model (indoor and outdoor temperatures, solar irradiance, heating power) are measured, and the RC model parameters are deduced using parameter identification techniques to obtain the best fit for the model. A similar approach was employed in [32] to determine the parameters of a 3R2C thermal network using the least-squares method based on six days of training data, resulting in a root-mean-squared error (RMSE) of 0.62 degrees Celsius.

In Fig. 11, if we examine the power profiles that are adjusted to the baseline, we can notice an intriguing rebound

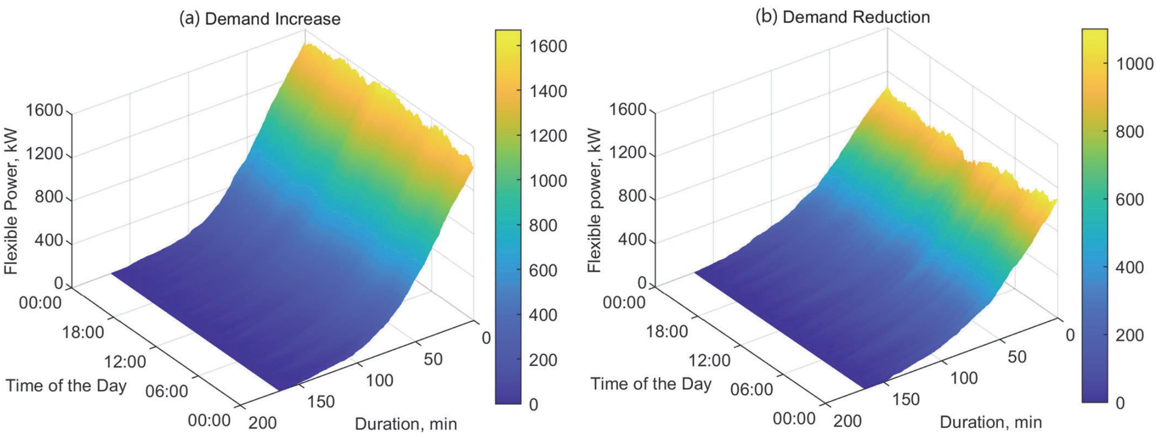

FIGURE 15. Heating system quantification curves for one day: (a) Demand increase, (b) Demand reduction.

overshooting effect. To the best knowledge of the authors, this effect has not been studied in previous research. For substantial flexibility activations, this rebound overshooting might be a significant factor that requires consideration.

The research conducted in this work can be expanded upon in future studies. This work used simplified models of heat pumps to illustrate the developed quantification process. In order to provide a more accurate estimate of the flexibility of heat pumps more comprehensive models are needed that account for the COP dependence on ambient temperature, different control methods, such as partial load operations, and temperature setpoint control for flexible operations.

Another possible direction is to also apply the quantification method introduced in this paper to other types of flexible devices, such as domestic hot water heating units, battery systems, and electric vehicles. The quantification method used in this study relies on knowing the current state of the device and its distance from boundaries. For instance, in the case of domestic hot water units, the flexibility can be measured by knowing the current water temperature and the maximum and minimum temperature limits. Similarly, in the case of battery systems, the current state of charge and the upper and lower allowed limits need to be known to quantify the flexibility.

Another possible research direction could involve forecasting flexibility. The flexibility quantification method presented in this paper could be developed further for flexibility forecasting by integrating weather forecasts and simulating temperature patterns for the next day. This would allow us to estimate, with a reasonable degree of accuracy, the future indoor temperature and how close it is to the upper and lower limits, enabling the creation of day-ahead flexibility power-duration curves. Fig. 15 shows surfaces created from power-duration curves of one day. From these surfaces it can be observed that heating system is able to provide consistent amount of flexibility throughout the day. This simulation was performed deterministically assuming perfect knowledge of influencing variables. For a reliable day-ahead flexibility forecast the uncertainty of weather forecast and models should be accounted for.

VI. CONCLUSION

This study introduces a novel approach to quantifying energy flexibility using power-duration curves to demonstrate the relationship between flexible power and its sustained duration. The quantification method is explained step by step, and a case study is conducted as an illustration. The case study involves modelling an aggregated portfolio of 1000 buildings with heat-pump-based heating systems. The results emphasise the significant impact of the asymmetry and non-linearity of energy flexibility. Specifically for heat pumps, they show that the power at which flexibility can be activated depends greatly on the activation duration, and there are noticeable differences between demand increase and decrease scenarios. This asymmetry suggests that energy flexibility behaves differently depending on whether power is being increased or reduced, which is a crucial factor to consider in energy management strategies. The study also brings attention to the rebound effect, where a heat pump-based energy system experiences a rebound response after flexibility activation that can be as much as 1.8 times the energy used during the activation. Additionally, the research identifies a rebound overshooting phenomenon, where the system oscillates before stabilising, that could potentially cause disturbances in grid stability. The observed asymmetry and non-linearity of energy flexibility emphasise the need for tailored demand response strategies that can adapt to varying conditions and flexibility sources. Future research should expand on these findings by applying the developed approach to different types of flexible loads and energy storage systems, developing flexibility forecasting methods, and further investigating the rebound overshooting effect and its implications for grid stability.

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Review article

Aggregated demand-side energy flexibility: A comprehensive review on characterization, forecasting and market prospects

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ABSTRACT

Existing grids have been designed with traditional large centralized generation in mind; however, with the ever-increasing utilization of renewable distributed energy resources, the challenges of proper grid management have intensified. Demand-side energy flexibility is seen as one potential way to alleviate these challenges. Presently, residential demand-side energy flexibility has remained a largely untapped resource since individual prosumers are too small to provide enough capacity, thus necessitating the need for an aggregator. In view of the aforementioned, this paper conducts a literature review on the aggregated residential demand-side energy flexibility. The paper gives an overview of characterization methods of energy flexibility. The sources of residential energy flexibility are identified and categorized based on their flexibility characteristics. In addition, the quantification methods and parameters of energy flexibility are analyzed. Moreover, the forecasting methods of energy flexibility in the context of different flexibility sources are outlined. Additionally, an overview of existing markets and potential new emerging flexibility markets is given. The challenges and barriers faced by the aggregators attempting to enter flexibility markets are examined. Finally, the paper is concluded by providing a discussion of the key findings that summarize the current research directions and highlight the gaps for future development of aggregated energy flexibility.

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1. Introduction

Due to the rising concerns about global climate issues, an increase in the usage of renewable energy sources (RES) has been reported. The share of energy from RES in electricity consumption of the European Union (EU) increased from 16.9% in 2008 to 32.1% in 2018 (Eurostat, 2020b). Thus, Variable Renewable Energy (VRE) sources such as wind and solar energy are increasingly integrated into the power grids. However, due to the fluctuating nature of VRE, more flexibility is needed to balance the varying supply and demand of energy (Lund et al., 2015).

Supplying for more than about 30% of annual demand using VRE can be challenging at the present levels of flexibility (Perera et al., 2019). In the study of Electrical Energy Storage (EES) requirements for Europe and the US (Cebulla et al., 2018), it was found that to achieve over 80% VRE penetration, an additional 1–3 TWh of storage would be necessary for PV-dominated grids and 0.2–1.0 TWh of storage for wind-dominated grids. Flexibility Tracker, an assessment methodology to estimate the readiness of existing power systems for high shares of VRE based on 80 standardized Key Performance Indicators (KPI), was developed in Papaefthymiou et al. (2018).

Energy flexibility sources can be broadly divided into two categories: demand-side flexibility and supply-side flexibility (Aduda et al., 2016). Conventionally, the power balancing has been handled on the supply side by varying the output of power generation units in response to changes in the demand. Supply-side flexibility is obtained by integrating power plants with different response times into the power grid. Based on their response times, power plants can be divided into base load power plants, load following (intermediate) power plants, and peaking power plants (Alizadeh et al., 2016).

Base load power plants (e.g., nuclear, coal, geothermal and oil-shale) provide continuous power to cover the base of the power demand as the name suggests. These types of power plants react slowly and are thus operated at constant power near nominal output levels for higher efficiency. They are typically only turned off for periodic maintenance, upgrading, and other major services. Intermediate load-following power plants (e.g., hydroelectric, wind, and solar) supplement base load power plants by enabling the transition between base load and peak load demand. These types of power plants react faster than base load plants and are not as expensive to operate as peak load plants. Wind and solar plants also fall into this category because their output depends on the weather conditions. They cannot cover the base without an effective energy storage system and nor can they be immediately employed in response to peak power demand. Peaking power plants (e.g., natural gas and oil plants, hydrofacilities) are operated during the daily peak power demands. This type of power plant is the fastest of the three; however, it is also the most expensive per MWh base.

Demand-side flexibility allows for reduction, increase, or shifting of electrical loads within short notice to balance short-term fluctuations in supply or to level out the demand profile in the long run. Demand-side flexibility sources incorporate the thermal mass of buildings, residential (Li and Pye, 2018), commercial (Aduda et al., 2017), and industrial (Heffron et al., 2020) flexible loads, whose consumption can be controlled to some extent within the users' comfort ranges. Controllable and flexible residential loads include air conditioning, water heaters, fridges, dishwashers, washing machines, battery storage systems, and electric vehicles. Characterization of residential flexibility sources is further discussed in Section 2. In commercial buildings, heating, ventilation, and air cooling (HVAC) and lighting are major consumers and are somewhat flexible within certain comfort and regulatory ranges, thus being a good source for energy flexibility. Sources of flexibility in industrial loads are case-specific, for example in the food or fishing industry, cold storage can be used as a source of flexibility (Heffron et al., 2020). Different price-based and incentive-based demand response (DR) programs can be used to control these loads (Palensky and Dietrich, 2011).

The uncertainty of available flexibility influences the effectiveness of DR programs and thus it is important to forecast flexibility. Available demand-side flexibility can be estimated by predicting the size of controllable loads from the load mix using load decomposition, i.e. disaggregation (Ponocko and Milanovic, 2018). Broadly, disaggregation can be divided into two categories: Non-Intrusive Load Monitoring (NILM), which uses a single monitoring meter, usually a smart meter and Intrusive Load Monitoring (ILM), which consists of measuring one or few appliances locally (Ridi et al., 2014). The forecasting of demand-side flexibility is discussed in detail in Section 3.

Assessing the flexibility of a system might be a difficult task, instead, the signs of inflexibility are sometimes more visible. Signs of inflexibility (Papaefthymiou et al., 2018; Cochran et al., 2014) include:

- Difficulty in balancing demand and supply that results in severe recurring frequency excursions.
- Significant renewable energy source (RES) curtailment due to transmission constraints or overproduction of conventional inflexible power.
- Negative market prices can indicate numerous types of inflexibilities, such as overproduction of inflexible power, excess of renewable energy, shortage of demand, and limited transmission capacity.
- Other signs include price volatility, high levels of redispatch, area balancing violations, loss-of-load, and subsidized overcapacity.

A single household on its own does not provide enough flexibility for grid improvement and might find it difficult to participate in markets due to its small scale. Thus, an aggregator is needed to build up a portfolio of many smaller controllable loads to act as a single entity. Aggregators serve as intermediaries between end-users and system operators (Burger et al., 2017). The aggregator offers their aggregated flexibility to the markets (e.g., wholesale, reserve, ancillary). The position and the roles of an aggregator are discussed further in Section 4.

In the literature, various parts of energy flexibility have been covered. For example, the technical parameters of distributed energy resources (DERs) and incentives for market operation have been provided in Eid et al. (2016). The flexible control of district heating and cooling networks has been reviewed in Vandermeulen et al. (2018). The quantification methodologies of energy flexible buildings with thermal storage case studies have been analyzed in Reynders et al. (2018). The concepts, models, and clearing methods of local flexibility markets have been assessed in Jin et al. (2020). The demand response (DR) incentives for efficient operation of distributed energy resources (DERs) have

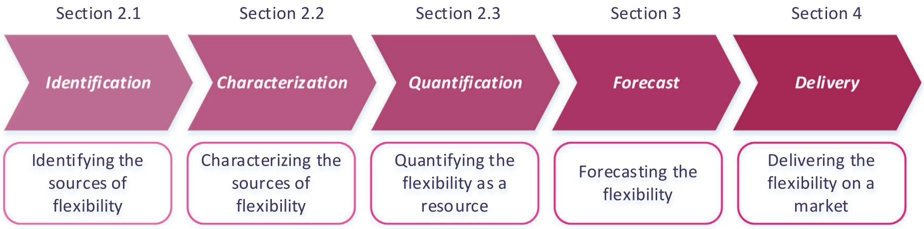

Fig. 1.1. Graphical description of the review paper topics.

been reviewed in Chen et al. (2018). However, there seems to be a lack of existing research that provides a comprehensive review of specifically aggregated residential energy flexibility. Thus, this paper attempts to bridge the gap by contributing to the existing research in the following manner:

1. This paper provides a comprehensive review of residential demand-side energy flexibility specifically in the context of aggregation.
2. Sources and characteristics of residential demand-side energy flexibility are identified.
3. The quantification methods and parameters are analyzed.
4. The existing and potential new emerging markets for aggregated energy flexibility are reviewed.
5. The barriers and challenges faced by the aggregators attempting to enter the market are examined.

This paper presents a review, classification, and discussion of many relevant aspects of aggregated residential demand-side energy flexibility. A graphical description of the review paper topics is given in Fig. 1.1. Section 2 provides an overview of characterization and quantification methods of aggregated demand-side flexibility. Section 3 outlines commonly used methods for flexibility forecasting. Section 4 is dedicated to the market aspect of aggregated energy flexibility and the barriers and challenges faced by the aggregators. Section 5 contains the discussion summarizing key findings and conclusions.

2. Characterization of flexibility

According to Jin et al. (2020) and Villar et al. (2018), flexibility products can also be divided into three different types based on which system (transmission or distribution) needs flexibility and from which system (transmission or distribution) it is procured:

1. Transmission network balancing flexibility procured by the transmission system operator (TSO) from the transmission system. Traditionally traded in fully developed intra-day energy markets or reserve markets.
2. Transmission network balancing flexibility procured by the TSO from the distribution system (Roos, 2017). The flexibility of this type is needed to support the flexibility trading of the first type. The TSO-distribution system operator (DSO) coordination is necessary here to avoid problems caused for the distribution grid by the flexibility services provided for the TSO (Hansen et al., 2013). The major driver for the development of a market for this type of flexibility is the TSO's need for flexibility from the distribution system.
3. Distribution network flexibility procured by the DSO from local DERs for local balancing, voltage regulation, congestion management, or losses reduction. The development of local flexibility markets (LFMs) is driven by the DSO's need for more active system management and control that provide the opportunities and trading environments for this type of flexibility. In this review, the third type of flexibility is addressed from the perspective of an aggregator.

2.1. Definition of flexibility

At this moment, there is no clear definition for energy flexibility. Many authors have attempted to define it based on their specific field of research. A general definition of energy flexibility of a building has been given in the IEA EBC Annex 67 project "Energy Flexible Buildings" (Pernetti Roberta and Søren Østergaard Jensen, 2019) as "The energy flexibility of a building is the ability to manage its demand and generation according to local climate conditions, user needs, and grid requirements. Energy flexibility of buildings will thus allow for demand-side management/load control and thereby demand response based on the requirements of the surrounding grids".

The newer IEA EBC Annex 82 project "Energy Flexible Buildings Towards Resilient Low Carbon Energy Systems" (IEA, 2022a) focuses on expanding the Annex 67 by considering the clusters of buildings and multi-carrier energy systems. Additionally, it aims to understand what would motivate the stakeholders to utilize such systems and what barriers prevent further participation.

Another IEA EBC Annex 83 project "Positive Energy Districts" (IEA, 2022b) aims to develop in-depth definitions of positive energy districts (PEDs), technologies, planning tools, and planning and decision-making processes related to PEDs. In the scope of this projects 60 existing European PED projects have been reviewed finding that most projects are in their early planning and implementation stages, illustrating the actuality of PEDs.

2.1.1. Properties of flexibility

From a technical point of view, electrical flexibility services can be defined as power generation or consumption adjustments starting at a given time for a given duration at a specific location in the electrical grid. Therefore, the properties of flexibility services can be expressed by their (a) direction (up or down, as in generation or consumption), (b) the amount of power that is adjusted, (c) the starting time, (d) the duration, and (e) the location in electrical grid (Jin et al., 2020; Villar et al., 2018; Eid et al., 2015), as shown in Fig. 2.1. Other frequently mentioned properties in the literature include controllability, predictability, time availability, delivering time, and cost (resulting cost or loss of efficiency from activating flexibility service).

- The **directional** property describes the power flow direction of the flexibility sources, whether they are generation or consumption types. Flexibility sources can be unidirectional 'up' or 'down', or bidirectional. Controllable household appliances, such as water heaters and washing machines, have a 'down' direction, meaning that they are consumers, while curtailable PV and wind generation have an 'up' direction, meaning that they are producers. Bidirectional flexibility includes sources such as battery storage or electric vehicles; they can act as both consumer loads and generating sources, i.e. prosumer capable loads.

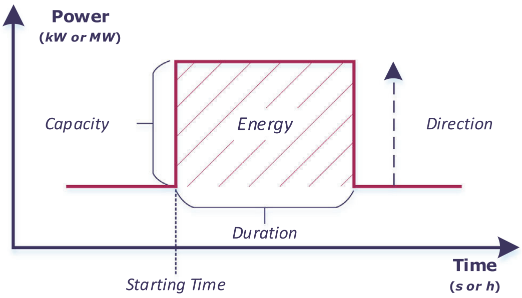

Fig. 2.1. Properties of a flexibility service (based on Roos (2017)).

- The **power capacity** property describes the power adjustment that a flexibility service is capable of modifying. Combined with the **duration** for which the flexibility service can be activated, the flexibility sources can be categorized as either capacity or energy type sources. Capacity type sources can activate for a short duration with high power, while energy type sources can be activated for a longer duration, however with smaller power output.
- **Starting time** property describes the delay from receiving the activation signal to when the flexibility service engages. In addition, some flexible sources can only be activated at a certain time of the day, either because the owner of the flexibility source has defined it as such or because of the intrinsic nature of the source.
- **The location** property describes the actual location of the flexibility source in the distribution grid. For the DSO, the location where flexibility is needed might be important to solve congestion problems, while for the TSO and balance responsive party (BRP), the location is less important since their objective might be to just balance the generation and consumption (Jin et al., 2020).

2.1.2. Flexibility function

Flexibility Function (FF) is a more complex characterization method that can be used to characterize energy flexibility that is controlled through the use of penalty signals. Penalty signals are external control signals that flexibility sources with penalty-aware controllers use to adjust their demand. The incentive is for the consumer to minimize their accumulated penalty. Depending on the reason or the objective of controlling flexibility, the penalty signals can represent different properties (Pernetti Roberta and Søren Østergaard Jensen, 2019), such as:

- **Real-time CO_2** emissions of consumed energy, in which case the flexibility controller tries to minimize the total carbon emissions and thus become emission-efficient.
- **Real-time electricity price**, in which case the goal is to minimize the total cost related to consumption and thus become cost-efficient.
- A **constant**, if the penalty is constant, then the flexibility controller simply tries to minimize the total energy consumption and thus become energy-efficient.

A penalty signal might be a combination of the above or constructed with other objectives in mind, such as reducing peak power consumption or to solve voltage, frequency problems, or manage grid congestions (Junker et al., 2019); in those cases, the location of the activated flexibility is also considered when a penalty signal is constructed.

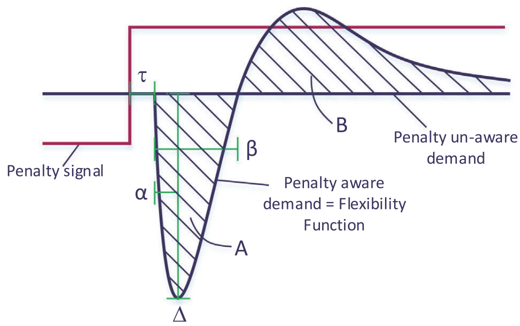

Fig. 2.2. Flexibility Function depicting the expected response of energy flexible buildings.
Source: Adapted from (Aduda et al., 2016).

FF was introduced in Junker et al. (2018) to describe the dynamic relationship between the penalty signal and a penalty-aware demand that responds to it. Commonly, energy flexibility is described using static functions for particular steady states that ignore the dynamics of changes, thus the FF attempts to describe the dynamic behaviors that arise from utilizing the energy flexibility. Observing the dynamics is important since activating energy flexibility inherently means deviating from normal operational set points. The FF can be constructed from the analysis of time-series data, through simulations, or from the first principles of a detailed model that includes constraints, occupancy behavior, controllers, and boundary conditions. An example of a FF is depicted in Fig. 2.2.

From the FF in Fig. 2.2, the energy flexibility can be characterized by the following parameters (Pernetti Roberta and Søren Østergaard Jensen, 2019):

- $\boldsymbol{\tau}$, the time delay from the adjustment of the penalty signal to the earliest response in demand. The delay can be attributed to communication delays or in some cases due to heavy computation in optimization algorithms. Also, some appliances might need time to finish their current operations before they can be turned off.
- $\boldsymbol{\alpha}$, the time it takes for flexibility to fully activate from initial change. This is affected by the reaction speed or the energy inertia of the flexibility source.
- $\boldsymbol{\beta}$, total amount of time for which the flexibility can be activated, which depends on the energy capacity of the flexibility source. For example, large heavy buildings that are well insulated can have large values, while smaller poorly insulated building cannot deviate their demand for too long.
- $\boldsymbol{\Delta}$, maximum demand adjustment, which describes the power capacity of the energy flexibility source.
- $\boldsymbol{A}$, total amount of energy that the flexibility source is capable of reducing (or increasing) in demand before reaching constraints set by the owner of said flexibility source. It is an important parameter if the reason for activating flexibility requires shifting a lot of energy.
- $\boldsymbol{B}$, total amount of energy needed to rebound back from the deviation caused by the previously activated flexibility. It depends on the type of the flexibility source, for example, if the heating is turned off to reduce demand, then afterwards it needs to be turned on again to return to the original temperature. However, when lighting is dimmed, then afterwards it is not needed to increase the brightness above the normal levels; in such case, there is no rebound.

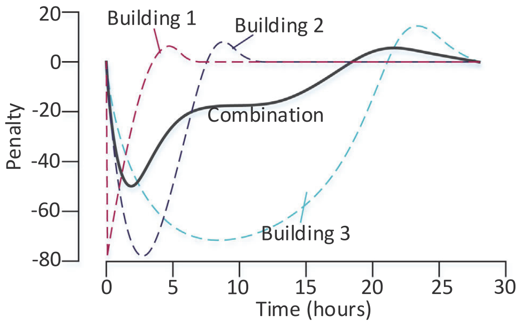

Fig. 2.3. Flexibility functions of buildings with different energy inertia. *Source:* Adapted from Aduda et al. (2016).

FF can be used to characterize an individual or a combination of flexibility sources, i.e. a building or a combination of buildings. An example of FF for buildings with different thermal mass is shown in Fig. 2.3, where building 1 has a significant amount of thermal mass with a large rebound effect, building 2 is medium-sized, and building 3 is poorly insulated with resistive heating, the black line shows the combined FF of these buildings.

2.2. Sources of demand-side flexibility

Buildings have great potential to be used as a source of aggregated energy flexibility. The building sector in the EU accounted for approximately 40.3% of final energy consumption in 2018 (26.1% households and 14.2% service sector) (Eurostat, 2020a). The energy flexibility that a building can provide is affected by several factors (Junker et al., 2018):

- Physical characteristics of a building (its thermal mass, insulation, and architectural layout)
- Controllable loads that are present in the building (ventilation, heating, storage equipment, etc.)
- Implemented control systems that enable controllable loads to react to external signals (control or penalty signals based on electricity price, CO_2 emissions, etc. Dadashi-Rad et al., 2020)
- The behavior of the building occupants and their comfort requirements

Building energy loads were classified in the Annex 67 project (Pernetti Roberta and Søren Østergaard Jensen, 2019) into three categories based on their priorities and the requirements needed to shift or change their consumption:

- **Shiftable loads**, these loads can be rescheduled to off-peak hours with the use of a penalty signal. This type of load can be usually shifted or interrupted without influencing the occupant's comfort too much. Shiftable loads can also be divided into **shiftable profile loads** (which have a rigid energy profile that cannot be changed but can be moved, such as washing machines) and **shiftable volume loads** (which allow the energy profile to change within some limits, whereas the total volume must be met over some time period, such as charging devices) (Ottesen and Tomasgard, 2015).
- **Non-shiftable loads** are those that are not flexible and cannot be shifted regardless of the energy cost; this is mainly due to occupant requirements, for example, lighting, cooking appliances, computers, and television.
- **Other controllable loads** can be controlled with optimal control strategies by thermostatic control, fan speed control, or dimming (e.g., HVAC, water heaters, and non-essential lighting).

2.2.1. Residential flexible loads

Residential loads can be characterized by the appliance type in the context of flexibility as either storable, non-storable, shiftable, non-shiftable, curtailable, or non-curtailable loads (He et al., 2013; Mancini et al., 2019). This way, an appliance's potential to participate in demand response can be reflected in the load characterization. Starting from the most flexible loads to the least flexible loads, the residential loads can be first segmented into storable and non-storable loads. Non-storable loads can be further divided into shiftable and non-shiftable loads. Next, non-shiftable loads can also be divided into curtailable and non-curtailable loads. Non-curtailable loads can be considered as inflexible base loads that cannot be controlled as they are non-storable, non-shiftable, and non-curtailable.

- **Storable loads** have a decoupled power consumption from the end-use service through the means of batteries or thermal inertia. This type of loads stores electrical energy in some other form (thermal, electrochemical, etc.). Examples of this type of load are batteries, electrical heating/cooling (HVAC) (Häring et al., 2021), and domestic hot water (DHW) appliances that store energy in a thermal mass.
- **Shiftable loads** are loads that have temporal flexibility in the sense that they can be moved in time, rescheduled to be activated later or earlier. Shiftable loads need to be planned in advance since they often have a predetermined operational cycle that cannot be interrupted. Washing machines, dryers, and dishwashers are some examples of shiftable loads.
- **Curtailable loads** cannot be shifted due to either the consumers' comfort needs or because there is no need to shift them, for example, there is no need to shift room lighting. However, curtailable loads can be interrupted if consumers are incentivized sufficiently.

An overview of common residential loads based on the above classification and their flexibility characteristics is given in Table 1. To assess the potential of flexible loads for aggregation, they can be characterized by whether they are capacity or energy type, by their response direction (unidirectionally upwards or downwards, or bidirectional), response speed, response duration, availability, and predictability (Eid et al., 2016).

- **Type (capacity or energy)** states the energy/power ratio of the flexible load. Those loads that have a low ratio can provide high power but are not able to maintain it for a long period of time and are thus more suitable to provide short-term flexibility services (e.g. ancillary services). In contrast, loads that have a high ratio can provide power for longer durations and can thus be considered as energy type loads and are better suited for longer applications, such as load leveling.
- **Response direction** determines the load's power flow direction. Some might be unidirectionally upwards or downwards, meaning that they either act as a load or a producer, but not as both. Bidirectional flexibility sources can act as a prosumer that at times consume power and at different times provide power back, such as battery storage devices.
- **Response speed** for residential flexible resources is generally quick in the order of seconds to minutes but it also depends on whether the load is available for flexibility usage.

Table 1
Characterization of residential flexible loads.

Appliance type	Storable appliances					Non-storable appliances		
						Shiftable appliances	Non-shiftable appliances	
							Curtailable	Non-curtailable
Flexibility characteristics	Electric Vehicles (EV)	Battery Storage (EES)	Heating and cooling (HVAC)	Domestic hot water (DHW)	Refrigerators	Wet appliances and dryers	Lighting	Cooking Devices and other 'must-use' home devices
Interruptible	Yes	Yes	Yes	Yes	Yes	No[a]	Yes	No
Capacity or energy type	Both	Both	Capacity	Both	Capacity	Capacity	Depends[b]	–
Response direction	Bidirectional[c]	Bidirectional	Downward	Downward	Downward	Downward	Downward	–
Response speed	Quick	Quick	Fast	Fast	Fast	Moderate	Quick	–
Response duration	Hours	Hours	Minutes	Hours	Minutes	Minutes	Hours	–
Availability	Evening and night	Always	Often	Often	Always	Rarely	Evening	–
Predictability	High	Perfect	High	High	High	Moderate	Good	–

[a]Wet appliances such as washing machines are interruptible for up to couple of minutes.
[b]New efficient low-power LED lighting systems are energy type while older less-efficient lighting systems are power type.
[c]With vehicle-to-grid technology EVs can respond in both directions.

- **Response duration** can be expressed as time for the maximum duration that a flexible load can sustain its power with respect to its nominal power when it is called upon. As stated in Eid et al. (2016), the response duration can sometimes be computed by dividing the allowed energy range with the maximum power capacity (for a 50 kWh battery with a 10 kW charging/discharging power, it would be 5 h). The response duration of flexible loads might be technology-specific and dependent on consumer behavior.
- **Availability** determines how often and when the load is available for flexible activation. Some devices, such as EVs, are usually available during the evening and nighttime since during the day, they would be parked away from residential homes. While others, such as wet appliances, could be available rarely as there is a specific time when there is an opportunity to activate them and only for once a day or so.
- **Predictability** expresses how accurately the availability of a flexible load can be estimated. Some loads can be very predictable like battery systems, while EVs are more likely to be available between 6 PM and 6 AM. Some loads, however, like washing machines and dishwashers, are less predictable since they are operated only a few hours a week and are subject to consumer behavior.

2.2.2. Distributed battery storages

Compared to unidirectional consumption type flexible loads, which can provide energy flexibility through the adjustment of their demand profiles, battery storages work bidirectionally as prosumer type devices. Battery storage systems can be excellent sources of energy flexibility due to their inherent nature of being able to store electrical energy for later usage.

Distributed battery storage systems are often installed together with PV systems as they can enable onsite self-consumption of PV power (Ahmadiahangar et al., 2022). Storing the excess energy from PVs for later use can reduce the loading of distribution grids during the peak demand time (Jankowiak et al., 2020) and mitigate the PV curtailment during low demand noontime when PVs are often overproducing (Segundo Sevilla et al., 2018).

For aggregators, distributed battery storages are a very important resource of energy flexibility since their response time is very quick, they can be immediately called upon, their state-of-charge (SOC) is always known, and their energy flexibility comes directly in an electrical manner, whereas for flexible loads, the energy flexibility is achieved through a roundabout control of temperature or scheduling of loads (Fischer et al., 2020).

Aggregated battery storage can be utilized for additional purposes that are not achievable for individual residential owners of smaller storage systems.

- If a high enough capacity for the aggregated battery storage is reached, then the aggregator can use it to participate in the reserve markets (Nitsch et al., 2021). Battery storage is ideal for this due to its fast response time.
- Aggregators can coordinate the energy flow of battery systems in a community, i.e. the energy sharing concept, to further increase the self-consumption of renewable energy, Riesen et al. (2017), or for local power balancing (Plaum et al., 2020) and peak shaving (Wang et al., 2019b) that reduces the ramping stress of conventional generation.
- Aggregated battery storage can provide additional ancillary service support (Sanjareh et al., 2021), such as distribution grid congestion management (Agbonaye et al., 2020) and black start support (Choi et al., 2021).

2.2.3. Electric vehicles

With the ever-increasing employment of electric vehicles (EVs), substantial research has focused on their utilization as flexibility sources. Compared to stationary battery systems, EVs have more nuanced considerations to keep in mind. Their inherent mobile nature can be considered in some circumstances either as a beneficial characteristic or as a drawback.

The mobile aspect of EVs means that they can travel between different parts of the grid. From the perspective of residential energy flexibility aggregators, this means that they might not always be present as their owners use them to commute to different locations. Due to this reason, overnight charging has been a large focus on the research of residential EV energy flexibility (Jian et al., 2017). The advancement of non-residential charging infrastructure will be the key to utilizing daytime charging as a flexibility source.

Since most EVs are parked and not operated for roughly 22 h a day (Brooks, 2003), they could be put in use for other purposes during that time, such as demand response, ancillary service provision, on-site use of renewable generation, and peak shaving. However, all these potential applications require an intermediate aggregator to engage EVs in these use-cases.

The research surrounding EV flexibility has mainly focused on optimal scheduling and optimization strategies of charging and cost minimization; often studied in the presence of renewable generation (Palmiotto et al., 2021; Wang et al., 2021).

Unidirectional charging is not all that EVs are able to provide, as together with smart charging infrastructure, the vehicle-to-grid (V2G) possibility becomes available, rendering EVs as bidirectional devices. V2G technology adds additional flexibility, as the EVs are then able to both charge and discharge, essentially becoming mobile battery systems. Although, V2G needs to be done under the considerations of battery degradation. Providing frequency containment reserve (primary reserve) can add an additional 1%–2% degradation to the typical 7%–12% capacity reduction over 5 years (Calearo and Marinelli, 2020). According to Bhoir et al. (2021), providing the combination of frequency containment reserve and peak-shaving is more profitable than providing either of them individually.

Frequency regulation using residential EVs was investigated using a dynamic relationship between the state-of-charge and the frequency setpoint in Muhssin et al. (2021). In a similar study (Meng et al., 2016) with droop control, it was also found that the bidirectional power regulation potential during the day was about one-third of that from during the night due to the lack of parked cars in the residential grid.

An outline in LaMonaca and Ryan (2022) provides the markets of EV charging infrastructure, with a focus on the existing charging types, the main market functions and actors, and future policy actions needed for widespread EV development.

2.3. Quantification of flexibility

As previously mentioned, there is no single commonly agreed-upon definition for energy flexibility. The definitions in the literature are usually worded in an abstract, vague manner and do not necessarily provide a means to quantify the amount of flexibility a given system or a flexible load has. An overview of the definitions of energy flexibility in the literature is given in Pernetti Roberta and Søren Østergaard Jensen (2019). When traded on flexibility markets it is a resource with a price tag and when aggregated on a large scale it can be used to affect electrical grid parameters, such as voltage and frequency. Thus, for real-world purposes, it is important to be able to quantify flexibility in a meaningful, quantitative manner. Quantification methodologies of thermal storages have been reviewed in Reynders et al. (2018) and Bampoulas et al. (2021).

In the literature, many quantification methods are used for energy flexibility. However, no one best quantification method fits every use-case, thus the method of quantification depends on the type of flexibility that is being quantified, i.e. storable, shiftable, or curtailable.

2.3.1. Flexibility envelope

A methodology proposed in D'hulst et al. (2015) is based on a flexibility envelope concept where energy flexibility is quantified by the possible power increase or decrease for the duration it can be sustained until constrained operational limits, e.g. user comfort and system constraints are reached. The concept of this quantification methodology is illustrated in Fig. 2.4, where flexibility is used to (a) increase power consumption and (b) decrease power consumption.

The lines $E_{\max}$ and $E_{\min}$ depict upper and lower energy bounds that represent two extreme scenarios. The upper energy bound

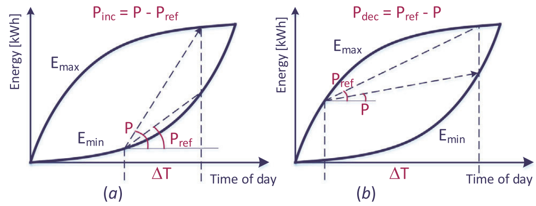

Fig. 2.4. Concept of the envelope quantification method: (a) flexible increase and (b) flexible decrease in power consumption.
Source: adapted from D'hulst et al. (2015).

is obtained when all devices are set to consume as early and as much as possible. This high-power consumption will continue until user comfort and system constraints are approached, e.g. room temperature reaches a specified upper limit and heating is turned off or schedulable appliances, such as washing machines, end their cycle and there is no need to turn them back any time soon. Likewise, the lower energy bound is obtained when all devices are set to consume as late and as little as possible. This time, the operation of devices is postponed as long as possible until lower constraints are approached, e.g. domestic water heater becomes too cold or the latest deadline when dishwasher should turn on is reached.

The available flexibility of a building or an individual device is determined by the current energetic status, "how far" it is from the limits imposed by the constraints, and the available time until the constraints or a set specific status is reached. Thus, in Fig. 2.4, the energy flexibility is quantified by the combination of possible power increase P_{inc} or decrease P_{dec} and the time interval ΔT this power change can be sustained until constraints are reached. P_{ref} signifies the reference power consumption, i.e. the power consumption at the time when energy flexibility usage is started and P is the maximal or minimal power consumption that does not violate constraints for the duration specified by the ΔT.

The drawbacks of this methodology are that it assumes that the initial and final states of the system are specified. Also, it is pointed out in D'hulst et al. (2015) that this quantification methodology is more of an indication of flexibility potential, rather than a tool for scheduling or rebound effect calculation.

This quantification methodology was used in Gasser et al. (2021) to quantify the flexibility of a house using a rule-based controller and model predictive controller with cost-oriented, emission-oriented, and flexibility-oriented objectives.

The flexibility envelopes were expanded in Azizi et al. (2021) to include NILM for the disaggregation of Shiftable appliances from the total consumption. The results of the study indicated that NILM integrated quantification method was able to extract the energy flexibility with 90% similarity to actually available energy flexibility. The aggregated energy flexibility characterization was improved by 40%.

2.3.2. Nodal operating envelope

A framework is presented in Riaz and Mancarella (2021) to model, describe, characterize, and quantify DER flexibility based on the concept of a nodal operating envelope (NOE). The NOE describes the feasible operating region of a device or a system under different constraints, meaning that this quantification method can be used to determine the network-feasible energy flexibility, contrasting other quantification methods that usually completely disregard network constraints. With this framework, the key flexibility metrics — capacity, ramp, duration, and cost, are quantified using the capability, feasibility, ramp, duration, economic, technical, and commercial flexibility features. These flexibility features

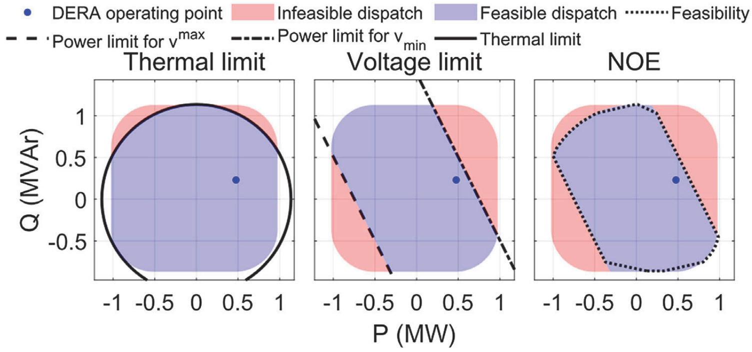

Fig. 2.5. Nodal operating envelopes in PQ plane (*capability* — the combination of red and blue regions, *feasibility* — blue region in NOE figure) (Riaz and Mancarella, 2021). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

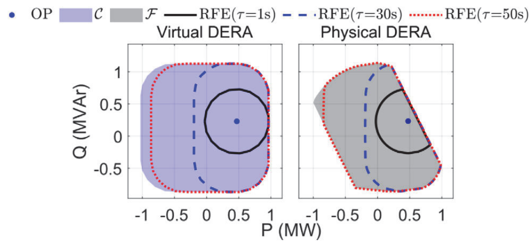

Fig. 2.6. Ramping flexibility (OP — operational point, C — *capability* region, F — *feasibility* region, RFE — ramping flexibility envelope, τ — ramp time) (Riaz and Mancarella, 2021).

are mapped in an active–reactive power space (PQ-space). The aggregated flexibility is estimated using Minkowski summation over the individual DER P-Q regions.

This methodology distinguishes between virtual and physical flexibility. Virtual flexibility is described as the *capability* operation region of the DER to provide flexibility regardless of the network constraints encountered in real implementation. Physical flexibility is described as the *feasibility* operation region that is obtained when the *capability* operation region is constrained by the network and other constraints, as shown in Fig. 2.5.

Different techno-economical aspects of distributed energy resource aggregation (DERA) flexibility can be quantified as possible operating regions using other nodal operating regions. For example, the *ramping flexibility* can be quantified with contours on these regions indicating the maximum active and reactive power that can be called upon based on the required ramp rate, as shown in Fig. 2.6.

These envelopes can be made to also quantify other flexibility features. The *duration flexibility*, which shows how long the flexibility activation can be sustained. The *economic flexibility*, which describes the cost of activating flexibility for a specific time. The *technical flexibility*, which is the ability to deviate from the current operational point with regard to the time and duration constraints. Lastly, the *commercial flexibility*, which is required to partake in the market with considerations to techno-economic constraints of time, service duration, and anticipated clearing price. Example envelopes for these flexibility characteristics can be found in Riaz and Mancarella (2021).

2.3.3. Quantification parameters

In numerous papers, no real systematized quantification methodology is used. Instead, flexibility is quantified using many different parameters describing electrical, time, comfort, cost domains. The parameters used to quantify energy flexibility are given in Table 2. Flexibility was observed to be quantifiable with three main dimensions: power [kW], energy [kWh], and time [h]. Depending on the use-case or the context, these dimensions can describe completely different properties, for example, duration and regeneration time are both time characteristics.

- **Power** dimension describes the capacity [kW] of the flexible loads. This is the main parameter for flexibility sources with power regulation capabilities, such as dimmable lights. Power dimension parameters found in the literature include instantaneous power flexibility, maximum power, mean power, maximal charging power, and power capacity.
- **Energy** [kWh] dimension is the main parameter for storable loads or volume shiftable flexible loads. Different energy parameters found in the literature include shiftable energy, energy reduction, energy capacity, storage capacity, and available storage capacity.
- **Time** [h] dimension is important to quantify flexible loads that are schedulable or with a shiftable profile. For example, starting and ending time of the washing machine and the duration of its operating cycle. Time properties discussed in the literature include the duration, comfort capacity, regeneration time, comfort recovery, maximum curtailment duration, and availability period.

Besides the main three flexibility quantification dimensions, others ways used to quantify flexibility are either through combined, relative, or other means.

- **Combined** parameters attempt to quantify flexibility as a function of two variables, for example, as a power shifting capability that gives a relation between change in power and the duration it can be sustained, or as a cost curve depicting the amount of shiftable energy and its associated cost.
- **Relative** parameters quantify flexibility as a proportion of two properties, these are self-consumption that is the proportion of demand covered by onsite generation or storage efficiency, relative peak reduction, DR potential, and battery SOC.
- **Other** parameters found in the literature are those that do not fit any of the above, such as coefficient of variation of power, ramping rate, frequency of operation, consistency of operation, peak time operation, and the potential score for how flexible a system is between 0 and 1.

Table 2
Flexibility quantification parameters in the literature.

Type	Parameter	Descriptions as given in publications	Ref.
Power [kW]	Instantaneous power flexibility	The potential power flexibility of TES and power-to-heat in any case of charging, discharging, or idle mode	Finck et al. (2018)
	Maximum power	The peak response after a trigger signal is sent	Fischer et al. (2017)
	Mean power	The corresponding mean power for the duration of an activation	Fischer et al. (2017)
	Maximal charging power	The EV station maximal charging power[a]	Zade et al. (2020)
	Average power curtailment	Average lighting power curtailment during the curtailable duration	Yu et al. (2020)
	Power capacity	How much power can be delivered as flexible power	Hurtado et al. (2017)
Energy [kWh]	Available storage capacity	The amount of energy that is shifted during optimal control	Finck et al. (2018)
		The amount of energy that can be added to the storage system, without jeopardizing comfort, in the time-frame of an ADR-event and given the dynamic boundary conditions	Reynders et al. (2017)
	Shiftable energy	The energy content below the curve; this energy can be consumed by the pool over the period of activation	Fischer et al. (2017)
	Energy reduction	How much energy can be reduced during a whole day	Yu et al. (2020)
	Energy capacity	How much energy can be delivered during the flexibility action	Hurtado et al. (2017)
	Storage capacity	The energy that can be added to the building thermal mass during a specific DR action	Bampoulas et al. (2021)
Time [h]	Duration	The time until the electricity consumption of the activated pool falls below the level of baseline operation	Fischer et al. (2017)
	Regeneration time	The time additional to the duration until the power consumption of the pool is back to normal	Fischer et al. (2017)
	Availability period	The time when EV is available for flexible usage[a]	Zade et al. (2020)
	Maximum curtailment duration	The sum of time in which the curtailment is possible during a whole day	Yu et al. (2020)
	Comfort capacity	How long the response can be sustained before the comfort limits are reached	Hurtado et al. (2017)
	Comfort recovery	How long the building requires to restore the nominal comfort	Hurtado et al. (2017)
Combined	Power shifting capability [kW, h]	The relation between the change in heating power and the duration that this shift can be maintained, taking into account the future boundary conditions	Reynders et al. (2017)
	Cost curve [kWh, EUR]	The amount of flexibility (shiftable energy) and its associated cost	De Coninck and Helsen (2016)
Relative	Self-consumption [%]	Proportion of increased demand covered by onsite generation during DR action	Bampoulas et al. (2021)
	Storage efficiency [%]	A measure of the energy cost associated with the specific DR action	Bampoulas et al. (2021)
		The ratio between discharging and charging events over the entire 24 h control horizon	Finck et al. (2018)
		The fraction of the heat stored during the DR event that can be used subsequently to reduce the heating power needed to maintain thermal comfort	Reynders et al. (2017)
	Battery SOC (%)	The state-of-charge of the (EV) battery[a]	Zade et al. (2020)
	Relative peak reduction [–]	Compares the deviation from the average of the minimum lighting power profile to the reference scenario	Yu et al. (2020)
	DR potential (%)	Potential power change during DR operation compared to baseline power consumption[a]	Yin et al. (2016)
Other	Coefficient of variation of power curtailment [–]	Determines whether the lighting system can provide a stable power curtailment capacity or a fluctuating capacity	Yu et al. (2020)
	Ramping rate [kW/min]	How fast the building reacts	Hurtado et al. (2017)
	Frequency of operation [0–1]	The ratio of the number of days that an appliance has been activated compared to the total number of historical days	Afzalan and Jazizadeh (2019)
	Consistency of operation [0–1]	The extent to which a user's behavior is deterministic or stochastic across subsequent days	Afzalan and Jazizadeh (2019)
	Peak time operation [0–1]	The energy consumption during the DR timeframe across historical days using min–max normalization	Afzalan and Jazizadeh (2019)
	Potential score [0–1]	Flexibility "score" based on the above 3 parameters	Afzalan and Jazizadeh (2019)

[a]Own descriptions based on the context of the work since the definitions were not provided in those publications.

3. Forecasting demand-side flexibility

For aggregators to participate in flexibility markets, they need to assess the resources in their portfolio, i.e. the available aggregated energy flexibility. Since the contracts on the flexibility markets will be made before the actual delivery date, it is crucial for aggregators to determine the amount of flexibility they can offer and which flexibility request to bid on by forecasting available flexibility in the future within reasonable uncertainty. However, flexibility forecasting is a complicated task, since it is influenced by customer behavior, consumption patterns, weather conditions, and other variables, which make it challenging to model accurately. In the interest of avoiding penalties from the failure to deliver the correct amount of contracted flexibility, the aggregators must also forecast how the customers react to flexibility activation signals (price signals) to determine that the correct amount of flexibility is indeed activated.

To the best knowledge of the authors, there are few papers in the literature that consider specifically the forecasting of residential demand-side energy flexibility. Research seems to be more oriented around load forecasting (Ponocko and Milanovic, 2018; Rajabi and Estebsari, 2019; Gurses-Tran et al., 2020; Hernández et al., 2013), which is not necessarily the same as flexibility forecasting. Flexibility is predicted in Vesa et al. (2020) for data centers engaged in demand response programs. The flexibility of virtual power plants is forecasted using machine learning techniques in Macdougall et al. (2016). Flexibility potential for DR in the industry is evaluated in Lee et al. (2020). Load forecasting of industrial machine tools is discussed in Dietrich et al. (2020). General estimation of flexibility potential is explored based on long-term historical data (D'hulst et al., 2015; Dyson et al., 2014; Bustos-Turu et al., 2015), or by surveys on customer readiness to participate in DR programs (Yamaguchi et al., 2020; Vellei et al., 2020).

According to Ponocko and Milanovic (2018), smart meter coverage of only 5% is enough to provide data to forecast the flexibility of a group of aggregated customers with high confidence. Furthermore, the flexibility profile of a group of aggregated customers is much more easily predicted than the flexibility of individual customers due to their stochastic nature (Ponocko and Milanovic, 2018; Heleno et al., 2015; Azizi et al., 2021).

An overview of the papers focused on flexibility forecasting is given in Table 3, where they are divided by the forecasting model type:

- **Deterministic** models assume certainty in the input parameters and thus rarely provide uncertainties in their forecasts.
- **Probabilistic** models where the aim of the forecasting is not to predict a single value, but the distribution of the possible available flexibility, meaning that the uncertainty of the prediction is inherently included.
- **Machine learning** models are implemented to learn customer behavior during DR and normal operations to estimate the potentially extractable flexibility.

In the literature, different methodologies have been used to approach flexibility forecasting corresponding to the first two checkmark columns from the left in Table 3. For example, some papers attempt to forecast flexibility in response to a price signal, meaning that the forecasting question is "What price incentive should be given certain hours away to extract the certain needed amount of flexibility?" and not "How much flexibility will there be available in certain hours away?". Papers using this type of method usually treat forecasting as an optimization problem and often include finding an optimal schedule for appliances.

Other methods found in the literature attempt to forecast flexibility based on real-time simulations (AhmadiAhangar et al., 2019), or historical data. Papers using this method usually attempt to extract information about controllable and uncontrollable loads from historical measured data.

Forecasting flexibility of shiftable loads (washing machines, tumble dryers and dishwashers, etc.) and thermostatically controlled loads (domestic water heater, space heating, HVAC, etc.) are most common in the literature. Storable loads, such as battery storage and residential electric vehicles, are rarely forecasted in the literature.

4. Demand-side flexibility aggregation

Resulting from the untapped energy flexibility potential, a new market participant called the aggregator has emerged. In the paper at hand, the aggregator of demand-side flexibility, i.e., demand aggregator (DA), is considered. The role of the DA is to pool together a portfolio of many smaller flexibility resources to act as a bigger unit since a single residential or commercial customer is typically not able to provide enough capacity to participate in the markets on its own. Thus, the DA provides an important service of transforming passive residential or commercial customers into prosumers by aggregating the energy flexibility of their controllable loads. The DA can provide substantial value to power systems. According to Burger et al. (2017), the DA may provide fundamental, transitory, and opportunistic value. Fundamental value is derived from the act of aggregation itself, transitory value refers to the temporary value created as the power system advances from previous regulations and technologies to the next more advanced ones, and the opportunistic value emerges in response to regulatory flaws.

4.1. Energy flexibility markets

4.1.1. Existing developed markets

Currently, aggregators can trade flexibility on markets that have been historically designed for conventional centralized power plants. A single residential household is thus unable to participate in these markets alone. Therefore, aggregators could potentially combine (aggregate) the flexibility of many smaller producers together and sell it on markets. The existing markets where flexibility can be traded are the day-ahead, intra-day, and balancing reserve markets. The first two are managed by power exchanges, such as Nord Pool or EEX, while the third one is operated by the regional TSOs. An in-depth overview of aggregators' participation in these markets is given in Okur et al. (2021).

The **day-ahead market** (DAM) hosts bidding for the buying or selling of the next day's hourly energy production. The bidding is usually closed at noon of the day before the delivery. This means that to participate in the DAM, aggregators need to be able to forecast the available flexibility for at least one day ahead within reasonable uncertainty. There has been a substantial amount of research done about the utilization of aggregated flexibility on DAMs (Rosin et al., 2020). Most papers in this field investigate profit maximization under different conditions using various methods. For example, a robust optimization model profit-maximizer aggregator of EVs is presented in Porras et al. (2020), where it was found that compared to stochastic and deterministic models, around 9%–15% and 60%–64% reduction in deviations from energy balance could be achieved using their model. An optimal day-ahead bidding strategy using a stochastic optimization model was developed to maximize the profits of an EV aggregator in Zheng et al. (2020). A marginal price-based coordination optimization model using mixed-integer linear optimization was developed in Ding et al. (2020) to coordinate two EV aggregators. A support vector machine-based forecasting model of aggregated smart household flexibility in the context of DAM is developed in Wang et al. (2020), which is continued in Wang et al. (2019a) by developing an optimal bidding strategy of load aggregators to reduce the financial risk related to price volatility. A robust optimization model to reduce the operational cost of smart household aggregators was proposed in Correa-Florez et al. (2018), in which a 5.7% reduction was achieved. An optimal bidding strategy for a multi-energy virtual power plant aggregator was developed in Zhao et al. (2021), in which around 5% of the costs were reduced. An optimal bidding strategy of a multi-energy DER aggregator was developed in Di Somma et al. (2019), using stochastic mixed linear integer programming for the day-ahead market.

Intra-day market (IDM) bidding is done on the day of delivery. Bidding on IDM can be done based on more accurate forecast information that is obtained closer to the time of delivery. Thus, participating in an intra-day market might provide a means to deal with the risk involved with an incorrect day-ahead flexibility forecast (Schwabeneder et al., 2021). An incentive-based DR program model was proposed for participation in both day-ahead and intra-day markets in Shahryari et al. (2018). The results of the study show that participating in the intra-day market is profit-wise comparable to participation in the day-ahead market. It was found that there is a lack of research in the field of aggregated flexibility provision in intra-day markets.

The purpose of the **balancing market** is to deal with frequency deviations due to imbalance issues or unexpected loss of generation, through procurement of reserve capacity (Hirth and Ziegenhagen, 2015). The EU commission has established a regulative guideline for energy balancing (European Commission, 2017) to harmonize European balancing markets. This regulation entails that all EU member states should at one point

Table 3
Flexibility forecasting models used in the literature.

Forecasting model type	Specific model	In response to a price signal	Based on historical data	Shiftable loads (washing machines, dishwashers)	Thermostatically controlled loads (TCL)	Batterystorage	Electricvehicles (EV)	National level (broad range of sources)	Ref.
Deterministic models	Mixed Integer Linear Programming (MILP)	✔			✔				Heleno et al. (2015)
		✔		✔	✔	✔	✔	✔	Rasouli et al. (2020)
		✔	✔					✔	De Zotti et al. (2019)
		✔		✔	✔				Ruiz et al. (2015)
		✔		✔			✔		Kotsis et al. (2015)
		✔	✔	✔	✔				Gorria et al. (2013)
	Algorithmic method		✔		✔				Muller et al. (2017)
Probabilistic models	Chance-Constrained (CC)	✔	✔					✔	De Zotti et al. (2019)
	Autoregressive integrated moving average (ARIMA)		✔		✔				Kouzelis et al. (2015)
		✔	✔				✔		Pertl et al. (2019)
			✔		✔				Kara et al. (2014)
	Data analysis based		✔		✔				Wang et al. (2018a)
Machine learning models	Neural Networks (NN)		✔	✔	✔				Ponocko and Milanovic (2018)
			✔		✔				Paridari and Nordström (2020)
	Support Vector Machine (SVM)	✔	✔	✔	✔				Wang et al. (2020)
	Support Vector Data Description (SVDD)				✔	✔			Pinto et al. (2017)
	Logistic Regression	✔	✔	✔					Neupane et al. (2018)
	Piecewise-linear regression		✔		✔				Wang et al. (2018b)

provide three balancing reserve products: automatic Frequency Restoration Reserve (aFRR), manual Frequency Restoration Reserve (mFRR), i.e. secondary and tertiary reserves, and Replacement Reserve (RR). In addition to these, the Frequency Containment Reserve (FCR), i.e. the primary reserve, is being voluntarily implemented across Europe.

The bidding on RR ends 1 h before the time of delivery and 30 min for the aFRR and mFRR (ENTSO-E, 2020). Therefore, on the one hand, capitalizing on the reserve markets can look promising to aggregators due to low forecast errors of near to real-time operation. However, on the other hand, participation in reserve markets requires flexible power to be deployed at a fast rate, since the required full activation time of aFRR is 5 min, mFRR is 12.5 min, and RR is 30 min ENTSO-E (2020). Aggregated energy flexibility of EVs for reserve markets has been investigated in Tian et al. (2020), Şengör et al. (2020), Farahmand-Zahed et al. (2020), Cui et al. (2020), Sarker et al. (2016) and Liu et al. (2021). Similar to DAM publications in general, the focus is on the optimization of profits through optimal bidding strategies using various optimization algorithms.

4.1.2. Emerging markets for flexibility

Local flexibility markets

Local flexibility markets (LFMs) are electricity trading platforms where flexibility can be traded in geographically limited areas, such as small cities and towns, districts, communities, or neighborhoods (Olivella-Rosell et al., 2018b). Local flexibility market models and clearing methods are reviewed in Jin et al. (2020); it was found that LFM participants can have overlapping positions, either DSO or aggregator could be the LFM operator or the aggregator could be its own BRP. Thus, LFMs can be designed to suit diverse conditions and regulations. Moreover, the coordination between LFM and the balancing market should be considered if the TSO procures flexibility from LFM through TSO–DSO coordination. The importance of TSO–DSO coordination is further emphasized in Minniti et al. (2018) and Villar et al. (2018).

One of the first large-scale DR demonstrations was conducted in the frame of the EcoGrid EU project that involved around 1900 residential customers where real-time prices were used to incentivize change in the demand (Ding et al., 2013). It was concluded that price incentives grant the DSO limited security since they do not require the loads to shift their consumption, only incentivize it. Moreover, pricing schemes penalize inflexible loads that cannot shift or change their consumption.

These shortcomings were addressed with the EcoGrid 2.0 project where flexible loads were aggregated together and traded on a fully functioning experimental LFM under real conditions (Heinrich et al., 2020). In that project, two types of services were defined to manage congestions in the distribution grid: capacity limitation services and baseline flexibility services. It was shown that these services can provide an additional safety net against network overloadings and outages; however, they are rarely needed. It was also pointed out that there are widespread shortcomings and unrealistic assumptions in the literature. Rarely, clear definitions of flexibility services are given, meaning that presently no clearly standardized flexibility products are available. The same issue was also identified in the quantification section of this review paper where an overabundance of quantification parameters was seen, which illustrates the need for standardized flexibility products that would provide the outcome parameters of how the flexibility should be quantified to sell it as realistic flexibility products.

In Esmat et al. (2018), a decentralized LFM design that considers the uncertainty of the demand was introduced together with a right-to-use (RtU) option that would allow the DSO to reserve some flexibility that could be called upon in real-time if needed to manage potential congestions with medium probability. In Olivella-Rosell et al. (2018a), an LFM design was investigated where multiple flexibility services at the distribution network level could be provided. In the proposed framework, the aggregator manages the flexibility trading in the local energy community by acting as a local market operator. Twenty-three different European LFM design proposals for congestion management were evaluated in Radecke et al. (2019). According to the evaluations, most of the market design proposals do not pass the definition of a "market"; in addition, the product definitions, contract lengths, market clearing, and matching procedures were found to vary substantially between different designs.

Peer-to-peer trading

A novel concept of peer-to-peer (P2P) trading has emerged in recent years (Liu et al., 2017). The notion of P2P trading is to allow peers (prosumers and consumers) to directly trade energy between one another. This encourages the local consumption of excess renewable generation within the neighborhood. P2P trading can be used as a way to involve end-users in energy trading since unlike in traditional capacity and balancing markets, there are no minimum capacity requirements in P2P trading. However, there is no consensus on which market design, e.g. trading schemes, clearing methods, market-regulatory mechanisms, or business models, should P2P trading employ.

Studies in Zhang et al. (2018) identified key elements and strategies involved in P2P energy trading by composing a three-dimensional system architecture. In the first dimension, the interoperable exchange of information is facilitated between the power grid layer, the ICT layer, the control layer, and the business layer. In the second dimension, the size of the peers is considered, i.e. premises, microgrids, cells, and regions. In the third dimension, the time sequence of P2P trading is expressed as a bidding, energy exchanging, and settlement processes.

There have been multiple real-life demonstration projects involving P2P trading, such as EnerChain (EnerChain Website, 2021), Electron (Electron Website, 2021), Piclo (Piclo Website, 2021), SonnenCommunity (SonnenCommunity Website, 2021), Vandebron (Vandebron Website, 2021). An overview of these and other P2P projects is given in Zhang et al. (2017), Park and Yong (2017), and (Sousa et al., 2019). A trading platform called "Elecbay" was designed in Zhang et al. (2018) to facilitate P2P trading in a grid-connected LV microgrid. According to that study, increased diversity of energy consumers and prosumers can increase local generation and consumption balancing.

In Long et al. (2018), three different P2P market designs were proposed: bill sharing, mid-market rate, and auction-based pricing strategies. It was found that at a moderate level of PV penetration, the P2P trading would result in a reduction of the energy cost of around 30% for end-users. As reported in Lüth et al. (2018), the utilization of P2P trading resulted in 16% savings and coupled together with centralized or decentralized battery storages, the P2P trading resulted in 24% and 31% savings respectively.

The study in Sousa et al. (2019) focused on three different P2P market designs: full P2P market design where peers negotiate trades directly with each other; community-based market design where a community manager manages inter-community trading and is the middle-man between the community and the rest of the system; hybrid P2P design that combines previous two designs where there is a hierarchy of different layers and direct trading is performed between the peers on their layer. The paper concluded that the hybrid P2P market design is a good middle-ground, providing suitable scalability and giving room for P2P interactions.

A hierarchical framework is proposed in Li et al. (2019) that enables P2P trading using smart contracts of blockchain technology in residential, commercial, and industrial sectors. It is noted that the implementation of P2P trading is faced with a challenge of scalability. To address the issue of scalability, the authors of Hashemipour et al. (2021) proposed a dynamic allocation of P2P clusters that create an optimal match between different load and renewable profiles that complement each other. The benefit of clustering was given as the increased scalability of P2P trading when the number of participants increases.

A comprehensive review on P2P energy trading is given in Soto et al. (2021) where the main areas of interest in the research are identified as the topics of (1) trading platform architecture, security testing, and scalability; (2) blockchain technology based transaction mechanisms; (3) game theory based modeling of participant behavior; (4) simulations to validate other main topics; (5) optimizations to maximize the economic benefit of peers, and lastly, (6) algorithms that implement previous main topics.

Selling energy efficiency

According to Behrangrad (2015), another business plan for aggregators could be to sell the excess energy efficiency (EE) to other entities that could not achieve the minimum legally required EE. This is due to the numerous emissions, environmental, and energy efficiency codes that generation stakeholders have to adhere to. If the achieved EE of the aggregated flexibility is higher than the legally required minimum, then the business model would have to liquidate this excess EE for profit. This type of DR business model has been referred to as "energy savings certificates (ESC)", "energy efficiency credits (EEC)", or "white tags" (Bertoldi and Huld, 2006).

4.1.3. Network-feasible operation

In any real-world implementation, the operation of aggregators should be network-feasible and respectful towards the network constraints. Maintaining the flexibility dispatching within network limits can be a difficult challenge since aggregators usually do not have access to the data about market bidding and the state of the grid (Attarha et al., 2020). This aspect is oftentimes ignored in existing research; however, some researchers have attempted to tackle it.

As previously discussed in Section 2.3.2, a quantification method based on nodal operating envelopes has been proposed in Riaz and Mancarella (2021) that can be used to determine the network-feasible energy flexibility. Research surrounding network-feasible bidding strategies oftentimes includes separate constraints for network parameters. For example, in Iria et al. (2020) a network constrained bidding optimization strategy is proposed to coordinate the aggregation of prosumers in a day-ahead and secondary reserve markets.

A framework for local energy and flexibility trading was proposed in Khorasany et al. (2022), in which prosumers first participate in P2P market energy trading. Then, the network constraints are checked by the DSO concerning the energy scheduling of prosumers. If the operation ends up being network-unfeasible, then the DSO calculates the flexibility needed to avoid network issues. At the end, prosumers form a community and participate in flexibility market with respect to DSO's request.

A bidding strategy has been proposed in Attarha et al. (2021) that aims to tackle the limitations of inelastic bids that do not reflect DER flexibility and bids that result in network-infeasible operation. A hierarchical control framework consisting of a utility controller, community aggregators, and multiple home energy management systems (HEMS) was developed in Utkarsh et al. (2022) to compute the optimal setpoints of DERs that results in network-feasible operation.

4.2. Barriers and challenges faced by aggregators

With the Internal Electricity Market Directive (European Parliament, 2019), the EU has acknowledged that in the future "*market participants engaged in aggregation are likely to play an important role as intermediaries between customer groups and the market*". Thus, they have adopted different regulatory guidelines (European Commission, 2017; European Parliament, 2019; European Commission, 2019) to encourage the Member States to remove discriminatory provisions and barriers regarding aggregators' access to electricity markets and their participation in ancillary services provision. However, it is up to every individual Member State to "*choose the appropriate implementation model and approach to governance for independent aggregation while respecting the general principles set out in this Directive*" (European Parliament, 2019).

The Clean Energy for All Europeans Package (European Commission, 2019) issued in 2019 set new rules with the aim to establish a modern design for the EU electricity market that is more flexible, more market-oriented, and able to integrate a greater share of renewables. Although it does not require the Member States to actively support aggregation business models, instead, it aims to ensure non-discriminatory market rules for the aggregators in hopes that once a "leveled playing field" is created, the innovative products and services will appear (Nysten and Wimmer, 2019).

According to the survey (ENTSO-E, 2019) conducted by the European Network of Transmission System Operators for Electricity (ENTSO-E) on ancillary services procurement and electricity balancing market design, there are still large differences between market designs of European nations. These differences may be due to the way markets developed in these nations historically, or stem from the electricity generation mix; some nations use fewer traditionally centralized large producers while others may use more renewables in a decentralized manner.

Due to the different market designs, the barriers for aggregators to participate in the markets also vary by nation. Barriers for aggregators in Denmark, France, Germany, and the UK were assessed in Borne et al. (2018); similarly, the barriers in Austria, Germany, and the Netherlands were explored in Poplavskaya and de Vries (2019), and the authors of Barbero et al. (2020) looked at the barriers in Belgium, Finland, France, and UK markets. Barriers to providing ancillary services in the U.S electricity markets were also assessed in Cappers et al. (2013). Barriers that discourage customers from engaging in demand response programs are discussed in general in Parrish et al. (2020).

A modular framework to assess the barriers of entry for DERs in primary and secondary reserve markets was developed in Attarha et al. (2020). The framework contains three modules in a hierarchical order, where the first module has more impact than the second module, which has more impact than the third. The first module contains "rules regarding the aggregation of DERs", such as the technical discrimination against aggregated resources, interoperability among DSOs, and aggregation level. The second module includes barriers from the "rules defining the products in the market", such as minimum bid size, time definition of products, distance to the real-time reservation, and symmetry of products. The barriers in the third module stem from "rules defining the payment scheme for grid services", such as the nature of payment and extra remuneration bonus for flexibility.

The work presented in Borne et al. (2018) was continued by the authors of Poplavskaya and de Vries (2019) and Barbero et al. (2020) who proposed their frameworks to classify the barriers for DER aggregators. From the framework developed in Poplavskaya and de Vries (2019), the barriers for aggregators to enter the electricity market can largely be classified as either market access oriented or auction configuration oriented, where market access oriented barriers include formal access requirements, administrative aspects, technical prequalification criteria, while auction configuration oriented barriers include bid-related requirements, time-related characteristics, and remuneration. The framework developed in Barbero et al. (2020) classifies barriers as either regulatory, technical or economic.

According to Borne et al. (2018), to support the participation of aggregators, the changes in rules should include: the reduction of the minimum bid size, more flexible definition of the period of delivery, whereas auctions should be held daily and it should be possible to deliver asymmetrical products. Studies in Poplavskaya and de Vries (2019) found that flexible pooling conditions, higher bidding frequency, and product resolution, and the authorization of non-precontracted bids could help to integrate DERs into the market, while (Barbero et al., 2020) showed that the minimum bid size, bid symmetry, and product resolution strongly affect the income of aggregators.

Relying on the work of previous authors, the barriers for aggregators have been categorized in the paper at hand as barriers stemming from the factors regarding regulatory framework, market aspects, economic barriers, and the technological implementation aspects of aggregation. The barriers are summarized in Fig. 4.1.

Regulatory framework barriers refer to a restraining set of rules that either forbid or inhibit the activities of aggregators. The entities that lay down these rules can be either governmental or regulatory agencies, TSOs, and other units with the power to do so. Examples showing where the regulatory framework barriers can stem from are:

- **Explicit discrimination against aggregated resources**: Rules may be established that provide priority to certain players such as large industrial participants. TSOs and DSOs may also prefer players who are connected to their region of the grid; however, in the case of aggregated resources, the portfolio can consist of units originating from different parts of the grid.
- **Inadequate definition of clear roles and responsibilities for market actors**: This is a critical barrier throughout Europe since it hampers free-market competition, increases risks for all actors, and enables the abuse of consumer rights (Smart Energy, 2015).
- **Prequalification requirements**: Balancing service providers need to pass prequalification requirements to verify that their units can technically deliver the products. Rules should be established that enable the pooling of DERs, otherwise, aggregators would need to prequalify each unit of their portfolio, which defeats the purpose of the aggregation itself as the intrinsic value of aggregation comes from the pooling of smaller resources.
- **Portfolio requirements**: Rules may be set that regulate the unit mix of aggregators' portfolios. Examples are the share of relatively uncertain sources such as vRES and flexible loads to the share of more certain sources like battery storage and conventional production or demand.
- **Additional agreements**: Aggregators may be required to obtain authorization from other market participants. For instance, consent may be needed from the energy supplier of a large consumer, or the BRP (Poplavskaya and de Vries, 2019).

Market aspect barriers refer to obstacles encountered from the market side as the aggregator wishes to make an offer for their flexible resources.

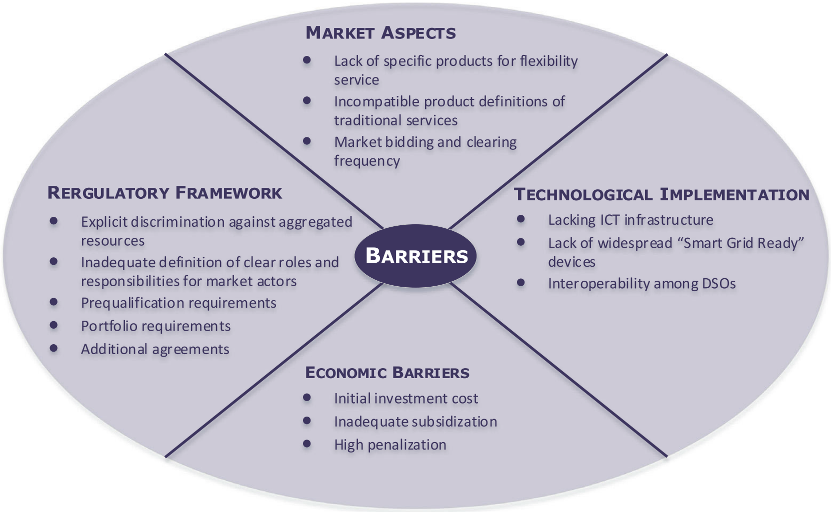

Fig. 4.1. Summary of barriers faced by aggregators.

- **Lack of specific products for flexibility service**: The rules of local flexibility markets (LFMs) have not yet been clearly defined, meaning that for now, aggregators are deprived of this source of revenue.
- **Incompatible product definitions of traditional services**: The specifications of conventional balancing products have been developed with the traditional generation in mind. Some of these specifications greatly inhibit the emergence of flexibility aggregators, for instance, the minimum bid size in most market designs is set too high for smaller aggregators to pass. The bid symmetry requirement effectively restricts the potentially usable flexibility resources, since flexible load-oriented DR aggregators have much more downward regulation potential. Other specifications that may affect the offering of aggregators' flexibility resources are temporal aspects, such as notification time, time to delivery, the duration of the delivery.
- **Market bidding and clearing frequency**: For balancing markets, the bidding and clearing frequency directly affects the duration for which the flexible resources should be reserved in case they need to be activated. If the bidding and clearing frequency is too low, then it will be difficult for the aggregators to reliably forecast their available resources beforehand, which reduces the aggregators' confidence in participation in these balancing markets (Smart Energy, 2015).

Economic barriers refer to barriers that impact the profitability of aggregation, some of these are:

- **Initial investment cost**: Unlike with conventional plants where the costs are well understood, the costs surrounding aggregation are not so clearly comprehensible. Aggregators of residential flexibility are faced with technical costs of smart meter installation, communication and control technologies that can accumulate into large initial investment costs. The 10 MW or more minimum bid size makes this especially relevant since aggregators would have to attract a large number of residential customers into their portfolio before they can even participate in the market and have a chance for returns.
- **Inadequate subsidization**: Peaking power plants are in direct competition to aggregated services. Subsidizing those plants can create an uneven playfield since they are already well established. It is the utilization of largely untapped energy flexibility resources that the aggregators provide that should be encouraged with subsidization.
- **High penalization**: A balance between production and consumption is essential to ensure system reliability, meaning that in the case of non-delivery they should be penalized. That said, penalties should not be excessively high to incentivize the inclusion of aggregated resources.

Technological implementation barriers refer to the hurdles that aggregators encounter when attempting to implement aggregation.

- **Lacking ICT infrastructure**: Technological implementation of aggregation relies on the presence of an adequate ICT infrastructure. Barriers of this kind can be loosely divided into sensing-related, computing-related, and communication-related (Good et al., 2017). Extensive metering and data acquisition are essential to determine the availability and forecast of flexible resources. A high level of smart meter penetration is thus crucial for aggregation. Processing a large amount of data is also computationally expensive, requiring large servers. The communication aspect requires data security and privacy to be ensured.
- **Lack of widespread "Smart Grid Ready" devices**: For the aggregation of residential energy flexibility, the devices (home appliances) themselves should be controllable over a data connection. The prevalence of smart devices is increasing; however, one important barrier is a lack of standardization in the software used to connect and control SG-ready devices.

Interoperability among DSOs: The technological implementation is also complicated from the grid-side since the portfolio of the aggregator can consist of units from regions operated by different DSOs. This is especially relevant for EVs that can cross from the region of one DSO to another within the same day (Borne et al., 2018).

5. Discussion and conclusions

Demand-side energy flexibility has remained a largely untapped resource. Not only could both prosumers and aggregators profit from selling energy flexibility, but it is also seen as an attractive alternative option to enhance grid reliability by managing the congestion and balancing problems. This paper presents a comprehensive literature review on the aggregated demand-side energy flexibility in order to give an overview of current research directions and highlight the gaps for future developments. In this paper, the properties and sources of aggregated energy flexibility were characterized. The quantification and forecasting methods were reviewed. The existing and potential new markets together with the barriers of entry for aggregators of energy flexibility were assessed.

It was found that there is no clear commonly agreed-upon definition for energy flexibility; however, it can be mainly characterized by the power capacity of the response, duration of the response, and the rebound effect. Many different methodologies are used in the literature to quantify energy flexibility. No one best methodology that fits all use-cases was observed, rather the employed method depends on the type of flexibility source that is being quantified whether it is a storable or shiftable type. An overabundance of quantification parameters was noted, illustrating that there is no one agreed-upon quantification method. This issue can also be observed from the market implementation perspective as the flexibility services and products are often given general descriptions such as "peak-shaving services" and "congestion management services", without specifying the exact parameters for those flexibility products. There have been LFM demonstrations such as EcoGrid 2.0 that have tried to address this issue by specifying the exact parameters for congestion management. However, further research is needed to develop clearly defined flexibility products for different use-cases, which would then provide the outcome of quantification methods for other researchers. The research for LFM and P2P trading is substantial as there are many different market designs, trading schemes, and clearing methods.

It is important for aggregators to forecast the available flexibility in their portfolio; however, from the conducted literature review, a lack of papers in this field was observed. Research seems to be more oriented around load forecasting, which is not necessarily the same as flexibility forecasting. Papers oriented around flexibility forecasting often attempt it through prosumer surveys or historical data to construct a more probabilistic estimation of long-term annual flexibility potential, which is a more general estimation than, for instance, short-term day-ahead forecasting.

Aggregators are faced with a diverse number of barriers and challenges. These challenges exist in the regulatory framework, technical implementation, and economic aspects. The regulatory laws relevant to aggregation are inappropriate or incomplete as the roles and responsibilities of future markets that include aggregators are not specifically defined. It is important to have some form of cooperation between aggregators, DSO, and the TSO since the activities of aggregators could cause potential issues in grid reliability. The technical implementation of aggregation would require not only smart grid-ready controllable appliances but also smart meters, which are still not widely implemented in many European nations. From the economic aspect, the future flexibility products are not properly defined yet and it might be difficult for aggregators to build a large enough portfolio to participate in current existing energy markets.

In summary, this review covers different aspects from the sources of flexibility, the methods of characterization, quantification, and forecasting, to the delivery on the present traditional markets, future potential flexibility markets, and explores the barriers and challenges faced by the aggregators. Based on the key findings of this review paper, the authors would like to provide the following suggestions for the direction of the future research:

- Researchers need to be on the same page when discussing their ideas, thus there is a need for research that provides an adequate, robust definition of energy flexibility.
- The end goal of energy flexibility lies in its utilization for some grid purpose, thus the delivery mechanisms, i.e. the flexibility product and services need to be properly defined.
- Delivering energy flexibility requires it to be properly quantified as a resource; therefore, further research is needed to provide quantification methodologies that are applicable for flexibility products and services.
- For aggregators to trade energy flexibility, they need to be able to forecast it into the future. A lack of research in the field of energy flexibility forecasting was noted.
- Future research should in general provide input to legislators to improve the regulatory laws that define the roles and responsibilities of parties that participate in the trading of energy flexibility.
- This review paper covers demand-side flexible loads and bidirectional sources. The energy flexibility of residential generation sources should be investigated to give an all-encompassing picture of residential energy flexibility.

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Data availability

No data was used for the research described in the article.

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Publication III

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Aggregated Energy Flexibility Provision Using Residential Heat Pumps

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***Abstract*—The rising relevance of such concepts as smart grids and demand response has led to power systems that are more closely monitored and managed. Utilization of demand-side energy flexibility, which is currently a largely untapped resource, is considered a potential way to alleviate challenges surrounding the integration of renewable distributed energy resources. In this paper, the aggregated energy flexibility of residential heat pumps was simulated. A resistor-capacitor thermal network in combination with a state-space model was used to model the thermal response of buildings. A total of 1500 different buildings were modeled as part of the aggregators' portfolio. Response to flexibility activation was simulated with two different controls depending on the strictness of consumers regards temperature comfort.**

***Keywords*—aggregation, energy flexibility, heat pump, thermal network**

I. Introduction

The phasing out of traditional generation with renewable distributed energy resources (DERs) has complicated the challenges surrounding grid congestions and frequency control since historically grids have been designed with traditional large producers in mind [1]. Demand-side energy flexibility has been seen as one potential resource that could be used to alleviate these issues through the management of flexible loads in consideration of the comfort requirements of consumers [2]. Currently, residential demand-side energy flexibility has remained a largely untapped resource.

Managing a single household does not provide enough energy flexibility for any tangible grid improvement. Therefore, it is necessary to aggregate the energy flexibility of many smaller buildings to attain the capacity needed to participate in wholesale, reserve, or ancillary markets for an effect on the electrical grid. The aggregator is supposed to serve as an intermediary between the owners of flexible loads and system operators [3].

Flexibility services provided by aggregators will surely become more relevant in the future residential grids. Oftentimes PV systems are installed in nearly zero energy buildings and modernized old buildings. As mentioned before renewable DERs can have a negative effect on the grid due to their fluctuating nature, thus it is vital for aggregators to provide local flexibility services to residential grids [4].

The residential loads that aggregators are interested in are those that are controllable and flexible in their operation [5]. This includes loads such as battery systems, heating systems, domestic hot water heaters, refrigerators, washing machines, dishwashers, etc. [6]. In this work, residential heat pumps are considered as a source of energy flexibility.

Based on the literature, building thermal energy models can be broadly divided into three different categories: white-box, grey-box, and black-box models [7].

White-box models are complex analytical models that rely on detailed thermodynamical equations for energy modeling. This type of model captures the dynamics of buildings well, however developing and solving them can be time-consuming. Due to this reason, white-box models might not be suitable for simulations that include a large number of buildings. White-box models are usually packaged into prebuilt software such as EnergyPlus [8] and IDA ICE [9]. An overview of strategies related to developing and simulating white-box models is given in [10].

Black-box models are extremely data-driven models that require extensive on-site measurement data to train models which can accurately predict the behavior of buildings under different conditions. Models of this type can be statistical or machine learning based models such as artificial neural networks, support vector machines, deep learning, and reinforcement learning based models [11]. Using black-box models for the simulation of aggregated energy flexibility of buildings is complicated by the requirement of extensive amounts of data that may not be available.

Grey-box models are a combination of analytical and data-driven models that include simplified physical equations. This combination provides a middle ground between the data requirement and computation efficiency. Due to this reason, a type of grey-box model called resistor-capacitor thermal network (RC-model) is used in this work to simulate aggregated energy flexibility of many buildings. RC-models are analogous to electrical circuits in the sense that they model thermal behavior with a circuit where resistors stand for thermal resistance and capacitors for thermal capacitance. Different types of RC-models, their parameter estimation, and applications have been reviewed in [12]. Accuracy comparison between RC-models with a different number of resistors and capacitors has been performed in [13], [14] from which it can be concluded that including the building envelope and inner mass into the model gives accurate results.

Research surrounding RC-models has been largely related to investigating methods of parameter estimation. This usually entails conducting *in situ* measurements of building construction dimensions, heating energy, indoor and outdoor temperature, and solar irradiance [15]–[17]. Thus, the novelty of this work stands in the utilization of RC thermal models for a purpose that is rarely used in the literature. To the best knowledge of the authors, very few papers have been published [18] that consider RC thermal models for aggregated energy flexibility.

The rest of the paper is organized as follows: Section II provides a description of the RC-model developed in this work. Section III outlines the simulation of aggregated energy flexibility and its results. Section IV concludes the paper.

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II. Model Description

A. Thermal Resistor-Capacitor Model of a Building

The thermal behavior of a building was modeled using an RC-model. This is a grey-box model that loosely incorporates the parameters of buildings related to their thermal dynamics, as opposed to white-box models that include very detailed parameters. Thermal RC-models are analogous to electrical circuits with resistors and capacitors that in this case represent the thermal resistance and thermal capacitance of different building elements.

In this paper, a 3R2C thermal model was applied that includes three thermal resistors and two thermal capacitors. The topology of a simplified thermal network implemented in this work is depicted in Fig. 1 which considers three different main components of a building: the building envelope (exterior walls), the windows, and the inner thermal mass (interior walls, furniture, and air). It can be seen that the outside temperature T_{out} influences the indoor temperature T_{in} through the exterior walls and the windows. The solar heating power is carried also through the envelope walls and the windows. A description of the inputs, outputs, and parameters of the thermal RC model is given in TABLE I.

In a thermal system with N elements a first-order differential equation can be constructed for each node n using the general heat-balance equation (1):

$$C_n \frac{dT_n}{dt} = \sum_{i \in N} \frac{T_i - T_n}{R_i} \Phi_n \quad (1)$$

where C_n and T_n are the thermal capacitance and the temperature of the element n, R_i is the thermal resistance between the elements i and n, and Φ_n is the sum of all heat fluxes applied to the node n [19].

From the above equation, it can be observed that the complexity of a thermal RC model can be varied by the number of elements that are considered. A more detailed model can be constructed by including many elements of different building components, e.g. construction and insulation layers of exterior and interior walls, roof, etc. Therefore, RC thermal networks are just models that can compose of a different number of resistors and capacitors and it is difficult to trace back in the literature the first instance of a 3R2C model.

Based on the thermal RC network topology shown in Fig. 1 and the heat-balance equation (1), the differential equations describing the temperature of inner mass (2) and the envelope (3) can be constructed.

$$\dot{T}_{in} = \frac{1}{R_{in}C_{in}} T_e - \left(\frac{1}{R_{in}C_{in}} + \frac{1}{R_w C_{in}}\right) T_{in} + \frac{1}{R_w C_{in}} T_{out} + \frac{1}{C_{in}} \phi_h + \frac{1}{C_{in}} \phi_{sol} A_w \quad (2)$$

$$\dot{T}_e = -\left(\frac{1}{R_{in}C_e} + \frac{1}{R_e C_e}\right) T_e - \frac{1}{R_{in}C_e} T_{in} + \frac{1}{R_e C_e} T_{out} + \frac{1}{C_{in}} \phi_{sol} A_w \quad (3)$$

The above differential equations can be used to simulate the thermal behavior of a building with the use of a state-space model (4) where A is the state matrix, B is the input

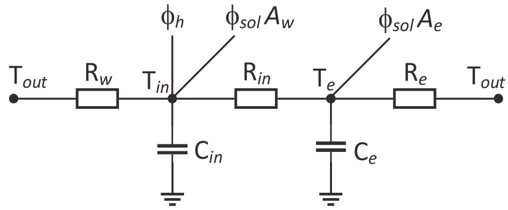

Fig. 1. Simplified 3R2C thermal resistor-capacitor network of a building

TABLE I. Description of Thermal Network Parameters

	Symbol	Description
Inputs	T_{out}	Ambient temperature, C
	ϕ_{sol}	Global horizontal solar irradiance, W/m^2
	ϕ_h	Heating power, W
Outputs	T_{in}	Indoor air temperature, C
	T_e	Envelope temperature, C
Parameters	R_e	Envelope thermal resistance, C/W
	C_e	Envelope thermal capacitance, J/C
	R_{in}	Inner mass thermal resistance, C/W
	C_{in}	Inner mass thermal capacitance, J/C
	R_w	Window thermal resistance, C/W
	A_e	Area of exterior walls, m^2
	A_w	Area of windows, m^2

matrix, C is the output matrix, and D is the feedthrough matrix.

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned} \quad (4)$$

In the context of the thermal RC model at hand, the above general state-space model representation (4) becomes (5):

$$\begin{bmatrix} \dot{T}_{in} \\ \dot{T}_e \end{bmatrix} = \begin{bmatrix} -\left(\frac{1}{R_{in}C_{in}} + \frac{1}{R_w C_{in}}\right) & \frac{1}{R_{in}C_{in}} \\ \frac{1}{R_{in}C_e} & -\left(\frac{1}{R_{in}C_e} + \frac{1}{R_e C_e}\right) \end{bmatrix} \begin{bmatrix} T_{in} \\ T_e \end{bmatrix} + \begin{bmatrix} \frac{1}{R_w C_{in}} & \frac{1}{C_{in}} & \frac{A_w}{C_{in}} \\ \frac{1}{R_e C_e} & 0 & \frac{A_e}{C_e} \end{bmatrix} \begin{bmatrix} T_{out} \\ \phi_h \\ \phi_{sol} \end{bmatrix} \quad (5)$$

$$\begin{bmatrix} T_{in} \\ T_e \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} T_{in} \\ T_e \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} T_{out} \\ \phi_h \\ \phi_{sol} \end{bmatrix}$$

B. Generation of Aggregated Buildings Parameters

The thermal behavior of buildings is influenced by many factors such as their size, level of insulation, construction materials, window-to-wall ratio, number of inner walls, etc. These factors can vary building-to-building. Thus, in order to investigate the aggregated energy flexibility of heat pumps, it is necessary to include various types of buildings in the simulation. Estimating the parameters of an RC-model for any specific building is a difficult process and to the best knowledge of the authors no publicly available database contains the amount of real building thermal network parameters needed to simulate aggregated control.

Therefore, these parameters need to be generated based on existing guidelines. From TABLE I, it can be seen that to model the thermal behavior of buildings 7 different parameters need to be generated for each of the buildings. The guidelines that describe the range in between these values lay for typical residential buildings are shown in TABLE II.

The building envelope was divided into two separate components, namely the exterior walls and windows. Three different types of residential buildings were considered in the terms of construction.

Light-weight buildings with exterior walls consisting of stucco, insulation, and plaster/gypsum. Medium-weight buildings with brick, insulation, air space, and gypsum layers. Heavy-weight buildings with brick, heavyweight concrete, insulation, and gypsum layers.

The thermal resistance and capacitance parameters of these building types were derived by the authors of [20]. The thermal resistance of windows was assumed to be that of typical double-glazed windows, while the thermal capacitance of windows was assumed to be negligible.

The inner mass of the building consists of inner walls, air, and furniture. The calculation guideline for their thermal parameters is given in ISO 52016-1:2017 [21]. Again three different weight classes were given also for the inner mass. For consistency, when generating building parameters, the same weight classes were chosen for both envelope and inner mass.

It can be observed that all of the thermal network parameters of the building envelope and inner mass are proportional to either the floor area A_{fl}, the exterior wall area A_e, or the window area A_w. This means that building thermal network parameters can be generated by sampling typical values for building constructional parameters [22], [23]. Based on the generated floor area A_{fl} and building height the area of the exterior envelope A_e can be deduced. Using the generated window-to-wall ratio the area of the windows A_w can be derived.

TABLE II. GENERATED BUILDING PARAMETERS

Envelope Thermal Network Parameters		
Class	$R_e\left(\frac{\mathrm{m^2C}}{\mathrm{W}}/\mathrm{m}^2\right)$	$C_e\left(\frac{kJ}{\mathrm{m^2C}}\cdot\mathrm{m}^2\right)$
Light-Weight	$3.1498/A_e$	$76.852\cdot A_e$
Medium-Weight	$3.8238/A_e$	$183.724\cdot A_e$
Heavy-Weight	$2.1917/A_e$	$402.102\cdot A_e$
Windows	$0.8333/A_w$	0
Inner Mass Thermal Network Parameters		
Class	$R_i\left(\frac{\mathrm{m^2C}}{\mathrm{W}}/\mathrm{m}^2\right)$	$C_i\left(\frac{kJ}{\mathrm{m^2C}}\cdot\mathrm{m}^2\right)$
Light-Weight	$0.13/A_{fl}$	$110\cdot A_{fl}$
Medium-Weight	$0.13/A_{fl}$	$165\cdot A_{fl}$
Heavy-Weight	$0.13/A_{fl}$	$260\cdot A_{fl}$
Building Size Parameters		
Floor Area, A_{fl}	$uniform(50, 200)$, m^2	
Building Height	$uniform(5, 12)$, m	
Window-to-Wall Ratio	$uniform(20, 50)$, %	

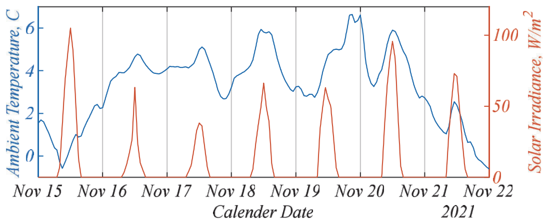

Fig. 2. Meteorological data used as model input

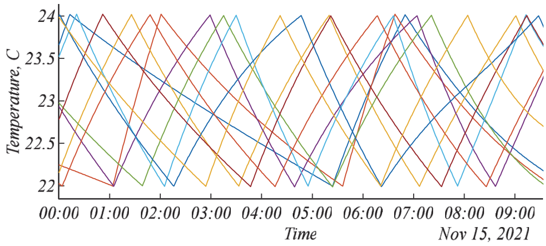

Fig. 3. Indoor temperature trajectories of 10 different example buildings, where each line represents one example building

III. AGGREGATED ENERGY FLEXIBILITY SIMULATION

A. Simulation Setup

It is possible to simulate the thermal behavior of buildings to assess the potential of aggregated heat pump energy flexibility using the simplified thermal network described in previous sections. The aim is to simulate a total of 1500 buildings that consist of equal amounts of light-, medium-, and heavy-weight buildings.

As described in TABLE II, the inputs of the model are the ambient temperature T_{out}, global horizontal solar irradiance ϕ_{sol}, and the heating power ϕ_h. Ambient temperature and solar irradiance were taken from real-life 1-week measurement data of Tallinn, Estonia in 2021 between 15th and 22nd November. This time period lies in the winter heating season with the outside ambient temperature between -0.6 C and $+6.6$ C as shown in Fig. 2. The heating power input was set as either 0 kW when the heat pump was off or between 6 and 12 kW when the heat pump was on depending on the size of the building.

The heat pumps coefficient of performance (COP) was sampled from a uniform distribution between 4 to 5, which is typical for residential heat pumps, dividing the heating power by COP gives the electrical consumption power.

The default non-flexible operation of heat pumps was modeled as hysteresis control with a ± 1 C deadband around the setpoint temperature. An example of temperature trajectories of 10 buildings is shown in Fig. 3 where it can be seen that for a setpoint of 23 C if the temperature drops to 22 C the heating system turns on until 24 C is reached.

B. Control Within Strict Comfort Range

The energy flexibility of the heating system was simulated with two different control methods. First, a simulation was conducted where the flexible operation was performed within a very strict comfort range set by the consumers that could not be violated even during flexible operation. This comfort range was set as ± 1 C around the setpoint 23 C. The control method in this scenario was a direct on-off signal.

Two energy flexibility scenarios were investigated: demand downregulation and upregulation. The results of this simulation are shown in Fig. 4. The flexible activation began at the simulation time of 17th November at 2 AM when the heating power was at a higher level than during the day due to no influence from solar heating. The flexibility activation signal was sent to all of the participants in the aggregator's portfolio. It can be observed that for a short period of time there was either an increase or decrease in the demand depending on the DR activation signal.

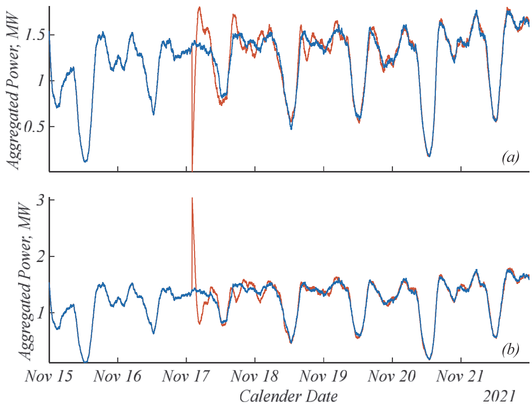

Fig. 4. Aggregated power regulation in strict comfort range scenario: (a) Downregulation; (b) Upregulation

C. Control With Setpoint Adjustments

The second energy flexibility control method was implemented through the adjustment of the indoor temperature setpoint. This scenario simulates the situation where the consumers in aggregators portfolio have less strict needs for temperature comfort range and allow short-term deviation of 1 C in either direction from the normal 23 C. This results in a setpoint of 24 C for demand upregulation and 22 C for demand downregulation. The results of this scenario are shown in Fig. 5.

D. Results

For both control methods, the heating systems responded appropriately. It can be observed from Fig. 4 and Fig. 5 that for downregulation the aggregated heating power dropped to almost 0 however, the demand reduction recovered within 1 hour for control within strict comfort range and within 4 hours for control with setpoint adjustments. This is due to a larger temperature decrease or increase potential attained with setpoint change. For demand upregulation, there was not as big of a difference as for control within a strict comfort range demand increase recovered within 2.5 hours and for setpoint control within 3.5 hours.

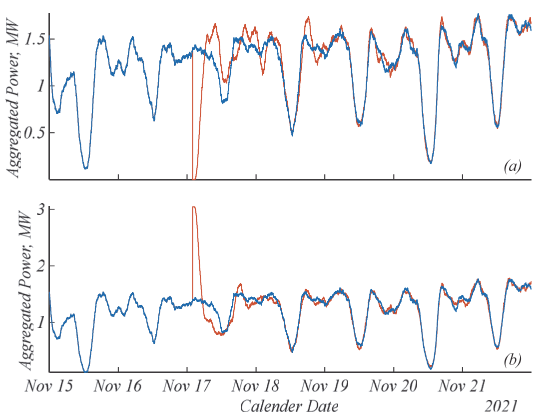

Fig. 5. Aggregated power regulation in setpoint adjustment scenario: (a) Downregulation; (b) Upregulation

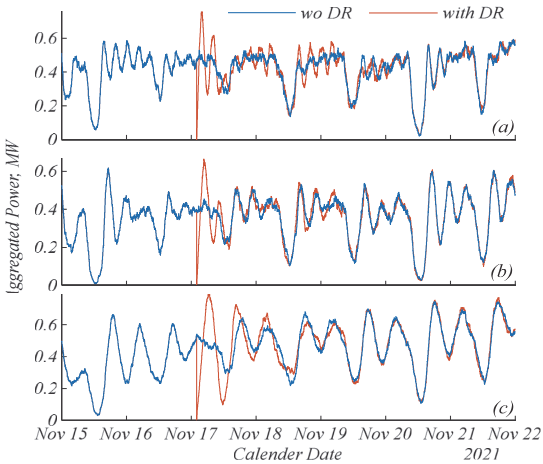

Fig. 6. Aggregated power of different building types: (a) Light-weight, (b) Medium-weight, (c) Heavy-weight buildings

The gradual recovery from energy flexibility activation is due to the difference between the temperature at the time of control activation and the lowest or highest temperature boundary as some buildings were already close to their allowed temperature bounds.

A "rebound effect" was observed after temperature recovered from the activation of energy flexibility resulting in demand change to the opposite direction from its activation direction. The rebound effect was similar in terms of capacity and length for both control scenarios.

It was observed that the activation of energy flexibility caused small deviations from the demand profile in subsequent days compared to the "business as usual" demand profile without flexibility activation. This means that any demand or energy flexibility forecasting algorithms should take into account disturbances caused by the activation of energy flexibility itself.

With 1500 buildings a 1 MW up- or downregulation could be sustained for around 1 hour. In order to facilitate demand response with higher capacity, the aggregator would either need to increase the number of heat pumps in its portfolio or integrate additional sources of energy flexibility into its portfolio such as domestic hot water units, shiftable wet appliances, or battery systems.

The difference between light-weight, medium-weight, and heavy-weight buildings is shown in Fig. 6. It can be observed that light-weight buildings have fast reaction speed and shorter, but more numerous oscillations in power draw. Heavy-weight buildings can provide flexibility for longer duration, but are accompanied by large power swings.

IV. Conclusions

In this paper, energy flexibility activation of residential heat pump systems was investigated. For this, a 3R2C thermal resistor-capacitor network in combination with a state-space model was used to simulate the thermal behavior of buildings. A total of 1500 different buildings were modeled that consisted of equal amounts of low-, medium-, and heavy-weight buildings. Two different energy flexibility control methods were simulated: first, flexibility activation with direct on-off control with a strict temperature comfort range requirement, and second, control through setpoint adjustment with a more relaxed temperature comfort range requirement. The activation of energy flexibility was modeled for both demand up- and downregulation. The results indicated that using setpoint control allows for longer energy flexibility activations due to a larger range for changes in indoor temperature.

Future work can include simulating flexibility activation with a specific capacity target in mind, e.g. 30% reduction in demand, this could be achieved by controlling the loads individually. Additionally, the forecasting of available energy flexibility could be investigated by determining the difference between building indoor temperature and temperature bounds.

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Publication IV

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Assessment of Power System Asset Dispatch under Different Local Energy Community Business Models

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Abstract: Community energy projects have gained popularity in recent years, and encouraging citizens to form local energy communities (LEC) is considered an effective tool for raising awareness about renewable energy. Since no single universal method exists for operating LECs, this study investigated the impact that different business models and asset dispatch methods have on LECs' economic and energy-related indicators. We carried out a case study, which included the development, modelling, and simulation of seven scenarios using mixed-integer linear programming (MILP). To measure and compare the prospective performance of the LECs in each scenario, six key metrics were evaluated and assessed. The authors find that simple, rule-based control systems might be well suited for LECs with a limited number of controllable assets that aim to provide increased levels of self-consumption of up to 3%. We also conclude that when the LEC utilises an energy cooperative business model, the selected asset dispatch method provides only minor differences in LEC performance, while for prosumer communities, the importance of selecting a suitable asset dispatch method is higher. We also conclude that LECs have the potential to significantly increase their economic performance by more than 10% by acting as aggregators and providing grid services directly to system operators.

Keywords: local energy community; asset dispatch; optimisation; energy management; battery energy storage; renewable energy sources; power system flexibility

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1. Introduction

Increased penetration of renewable energy sources (RES) is changing the structure [1], planning [2] and modelling [3] of the energy system. In this context, flexibility [4] or power smoothing approaches [5] aim to address the technical challenges arising due to the difficult-to-control nature of electricity generation from local RES. On a higher level, various local energy generation and distribution solutions, such as local energy communities (LECs), need to be analysed as well, where additional challenges arise in the fields of the economic validity of the local system and the desire of consumers to get involved in the creation of such a system. One of the ways to overcome these challenges is to use LEC optimisation methods [6]—Economic Load Dispatch (ELD) optimisation associated with appropriate business models [7,8]. Several authors have addressed these two aspects very extensively.

Regarding ELD, the authors in [7] developed an algorithm for stochastic load scheduling for local energy systems, thus providing an opportunity to model the future load and generation structures and to carry out further planning and development measures. Other publications have addressed ELD modelling with various optimisation methods: Ref. [8] by using two-stage stochastic mixed-integer programming with cost, balance, and flexibility constraints, where the cost could be reduced by up to 5%, Ref. [9] by proposing dynamic ELD, including demand response activities, variable renewable energies and storage systems, but Ref. [10] describes ELD as isolated local energy system by using Particle Swarm Optimisation. When looking at business models, a review of the literature on energy communities in [11] gives insight into energy community business model structures, aspects, and pros and cons from the consumer perspective. Authors of [12] reviewed emerging energy community-related business models, strengths, and barriers to energy community development.

Although recent publications provide innovative solutions for ELD, as well as for the analysis of business models and the possibilities of their use in specific LEC layouts, a lack of connection between ELD and business models can be observed. There is a significant research gap on the impact of relevant business models on ELD optimisation measures and their results on social and economic welfare.

To fill this gap, this paper aims to determine the mutual influence of business models and ELD optimisation on LEC economic and energy-related indicators (self-consumption, self-sufficiency, levelized cost of energy and revenues). Furthermore, results of ELD optimisation for different business models are provided with the help of case studies.

The paper is organised as follows: Section 2 describes power system asset dispatch methods and provides an overview of LEC business models, Section 3 includes the description of the conducted case study and studied object, Section 4 provides a detailed description of the modelled and simulated scenarios, Section 5 includes the discussion, and Section 6 summarises relevant conclusions.

2. Power System Asset Dispatch and Energy Community Business Models

2.1. Power System Asset Dispatch

In this study, the ELD problem is extended to enable objectives aside from economic costs and to include different types of dispatchable power system assets (e.g., energy storage systems). Power system asset dispatch is considered a general minimisation problem with constraints and can be written in the following form:

$$\min f(x), \text{ subject to } g(x) = 0, h(x) \leq 0, \tag{1}$$

where $f(x)$ is the objective function, $g(x)$ and $h(x)$ are, respectively, the set of equality and inequality constraints, x is the vector of control and state variables [13]. There are general constraints applied in this study:

- The battery energy storage system (BESS) cannot charge and discharge simultaneously.
- The power balance equation is described as an equality constraint (2):

$$P_{pcc,out} + P_{BESS,c} + P_{Prosumer} = P_{pcc,in} + P_{BESS,d} + P_{PV,prod}, \tag{2}$$

where $P_{pcc,out}$ is the active power exported from the LEC, $P_{BESS,c}$ the active power consumed by the BESS for battery charging, $P_{Prosumer}$ the aggregated active power consumption of all prosumers, $P_{pcc,in}$ the active power imported to the LEC, $P_{BESS,d}$ the active power produced during BESS discharging operation and $P_{PV,prod}$ the total active power produced by LEC photovoltaic generation plant (PV). However, there will always be some power loss, which is neglected by this equation.

The objective function varies based on the applied asset dispatch method. In this study, three different asset dispatch methods are investigated based on this general minimisation description:

- Maximisation of LEC self-consumption (LSC): If energy import from the grid can be minimised, the cost of buying additional energy is reduced. This minimisation of energy import means maximisation of self-consumption. For this minimisation method, the assets are shared equally in the community.
- Minimisation of levelized cost of energy (MLC): Shifting the import of energy to times with lower electricity prices reduces the cost of buying additional energy. Thus, this

method's minimisation goal is directly based on the imported electricity price instead of the electricity amount.

- Peer-to-peer energy trading (P2P): Like in the LSC method, minimising energy import to the LEC reduces the cost of buying additional energy. However, the P2P method considers the prosumers individually. There is a trading within the community where the prosumers try to reach their goals individually, maximising the energy matching within the community, which maximises self-consumption and minimises energy import.

2.2. Business Models Applied in Local Energy Communities

According to the authors of [14], new regulations and arrangements for electricity markets are necessary to encourage people to engage more in community initiatives and regional energy and power markets. Various business models may be applied in LECs. A comprehensive review of different LEC business models has been given in [12]. The following subsections give an overview of business models relevant to this study.

2.2.1. Energy Cooperatives (EC)

Energy cooperatives are one of Europe's most common energy community types [15]. According to the European Federation of citizen energy cooperatives, over 1900 energy cooperatives across the European Union member states have at least 1.25 million active customers [16]. Energy cooperatives are created through citizen-led initiatives where end-users fund the installation of local generation systems [17], as shown in Figure 1. Energy cooperatives can be run with many different organisational forms and financing models. Some are run as companies with profit-making in mind, where the shareholders finance medium to large-scale PV or wind power plants. Others can be non-profit organisations that finance local production of renewables to cover the self-consumption and the sale of surplus [18].

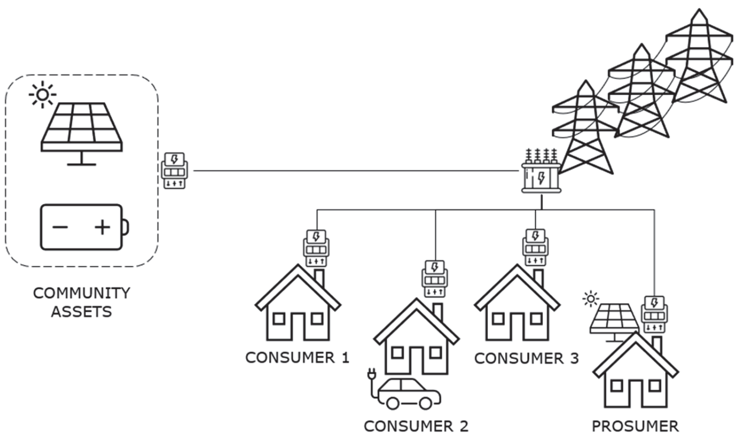

Figure 1. LEC organised as Energy Cooperative.

Energy cooperatives may be given the right to act as a sort of local distribution system operator (DSO) responsible for managing their low-voltage network. This operation enables them to exempt cooperative members from some of the use-of-system tariffs while incentivising self-consumption through dynamic pricing schemes and other billing conditions [19]. The roles that energy cooperatives may take are not standardised on the European legislative level and, thus, may depend on the regulations and network codes from country to country. For example, in Portugal, energy communities may be allowed to take over the responsibility of the DSO for the local community grid, while in the Netherlands, it is explicitly forbidden [20].

2.2.2. Prosumer Communities (PC)

Energy prosumer communities are often established by prosumers acting as decision-makers, investors, and customers. They cooperate to take advantage of favourable financing circumstances when buying assets in bulk and to acquire dimension for participation in flexibility markets, benefiting from collective energy efficiency (EE) initiatives or participating in local energy markets (LEM) [12]. In contrast to energy cooperatives, where end-users cooperate in acquiring medium to large-scale on-site generation, the prosumer community business model consists of individual small-scale prosumers in local communities, as depicted in Figure 2. These prosumers can act as decision-makers, investors, and customers. The source of revenue comes from trading their flexibility on LEMs, EE initiatives, and participation in flexibility markets [19]. Residents of the community sign a long-term public purchase agreement (PPA) with energy providers to sell the excess generation and purchase the leftover deficit energy. Members of the community can also trade energy among themselves (LEM or P2P trading), which relieves them of the obligation to pay fees associated with medium- and high-voltage distribution and transmission networks outside of their own grid [21].

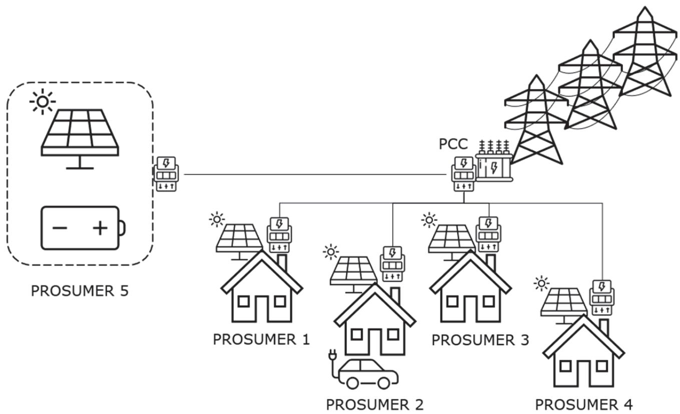

Figure 2. LEC organised as Community of Prosumers.

An example of community prosumerism includes the city of Litoměřice in the Czech Republic, where the local municipality and households financed a project that involved installing PV systems and energy efficiency measures to reduce the community's energy consumption from the main grid [12].

Prosumers are individuals who generate, utilise, and modulate their own renewable energy [19]. They include residential, commercial, and industrial entities [19]. The difficulties faced by energy systems are widely perceived as being resolved through prosumerism. In the light of this, the implementation of distributed energy systems (DES), in which energy is generated and consumed locally, is led by prosumers, lowering greenhouse gas emissions and assuring local value creation.

The advantages of energy "autarky" are emphasised by proponents, where various energy vectors, such as electricity, heating, transportation, and valuable work, may be obtained locally from sources such as solar, wind, geothermal, waste, and biogenic sources in increasingly closed-loop, circular systems. As a way to counteract the erratic nature of renewable energy sources, these scenarios also include demand-side behavioural changes such as storage and flexibility service offering and time-of-use (TOU) prices.

The necessity of new business models has been emphasised by several authors as a means of easing the transition to decentralized and prosumer-driven energy systems. These models may make it easier for people to use more renewable energy on their own, trade electricity locally, maintain the stability of the grid, and switch to other energy sources for heating and transportation. Limited number of studies have highlighted the various forms of value that such business models may produce as well as how they may be managed [22].

As per Ref. [23], the energy prosumer comprises two entities: the prosumer subject and its resources. The prosumer subject can be described as an owned who is proactive or its delegated manager (autonomous agent). The prosumer subject is responsible for formulating its strategic goals, e.g., emphasise renewable energy rather than minimise energy cost. The prosumer subject comprises of a well-informed agent, prosumer objectives, and requirements, and the prosumer assets are its financial assets, goods, and technology system.

Asset dispatch in CP energy communities can be performed with the following methods:

- Peer-to-peer energy trading;
- Maximising self-consumption;
- Minimising levelized cost of energy.

2.2.3. Community Flexibility Aggregation (CFA)

Due to its limited size and lack of flexibility, a single household does not offer sufficient flexibility for any significant grid enhancement and may find it difficult to engage in markets. When prosumers join, additional value may be created by aggregating their demand, supply, and energy flexibility. Thus, aggregation allows the prosumers to combine their resources, which allows them to gain more substantial leverage in negotiations with retailers and last-resort traders.

In addition to on-site RES, residential prosumers can find value in the intelligent management of smart appliances. These devices can broadly be divided into three categories [24]. Thermostatically controlled loads (TCLs) include space heating systems with smart thermostats and domestic water heaters (DHW). TCLs can be controlled within specific temperature ranges according to the prosumer's comfort requirements [25]. Shiftable appliances include wet appliances such as dishwashers, clothes washing machines, and drying machines. The usage of these devices can be shifted when there is a surplus of PV power or a cheaper electricity price. Storage devices such as battery systems can store surplus energy as electricity for later usage. In future electricity grids, electric vehicles (EVs) constitute a large share of local community energy demand that could be intelligently controlled. In the case of vehicle-to-grid (V2G) technology, the EVs can also provide bidirectional energy flow support and be considered a sort of mobile battery system [26].

The aggregation of residential community flexibility has many benefits. However, the real-world implementation would require consent from all aggregation participants and citizens might not have the technical skills or resources to implement this. In addition, cyber-physical infrastructure would become vital to facilitate the proper activation of devices and logging information related to billing purposes. Other aggregation challenges include legislative hindrances, such as the lack of clearly defined roles of the participant and the lack of definitions of flexibility services [27].

Communities formed with the purpose of aggregating power system flexibility aim to use demand side management (DSM) incentives to collectively and directly participate in flexibility services procured by system operators. CFA can also be realised through an aggregator that pools demand flexibility to reach sufficient volumes to make offers in reserve, balancing, or ancillary markets [28] or to an electricity retailer to balance its portfolio to avoid deviation penalties [29]. Residential demand flexibility is likely to become more appealing to businesses thanks to energy communities [30], while the author of [31] states that residential demand flexibility has already become economically feasible for LECs.

Compared with PC, the CFA business model does not expect all members to include energy production, as shown in Figure 3. Thus, their uptake is considered less costly and with lower complexity, meaning the technological infrastructure for such communities is easier to establish. For CFA-based LECs that are made up of residential dwellings, the flexibility pool consists of larger electricity consumers, e.g., heat pumps, electric vehicle (EV) chargers, and air conditioning (AC) units. The initiative for forming these communities might stem from aggregators [12] or property developers. A key enabler for forming such systems is the uptake of consumer devices that feature built-in functionality to participate in DSM incentives, e.g., OpenADR certified products [32], which reduce the integration cost of flexible loads.

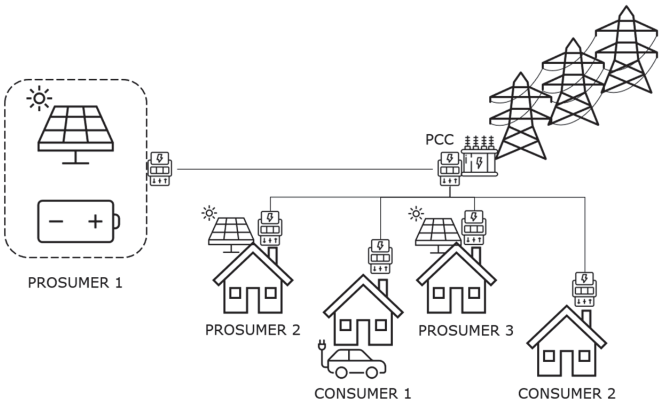

Figure 3. LEC organised as Community for Flexibility Aggregation.

LEC business models require different approaches for solving asset dispatch. A mapping of analysed asset dispatch methods that apply to more common LEC business models is provided in Table 1.

Table 1. Asset dispatch methods that apply to different LEC business models.

LEC Business Model	P2P	LSC	MLC
EC		✔	✔
PC	✔	✔	✔
CFA			✔

A case study is carried out to understand the economic performance of different asset dispatch methods under different business models.

3. Case Study and Object Description

Six scenarios are studied corresponding to the combinations of LEC business models and asset dispatch methods (Table 1). A benchmark simulation, which incorporates asset dispatch in the form of a robust rule-based controller for controlling a BESS, is also carried out for comparison. The topology of an actual segment of an electricity distribution system of a residential area in Riga is used. The generalised topology of the electric power system is depicted in Figure 4. To prevent possible breaches of privacy, the metering data used in the study is not collected from the same system. Instead, residential consumers and PV production plants' individually collected and anonymised metering data is mapped to the LEC power system nodes. The dataset used for the study has a time step of 1 h and a range of 3 years. The distribution grid used in the case study includes one common grid connection point (point of common coupling—PCC) and 53 nodes, from which 38 are plain consumers, and 15 are prosumers.

Additionally, a generic prosumer (denoted as P_x) is included in the system. The generic prosumer incorporates a larger (rated at 50 kW) PV production unit and a grid-scale BESS (rated at 75 kW, 200 kWh). The ownership and operation of prosumer P_x vary between different scenarios.

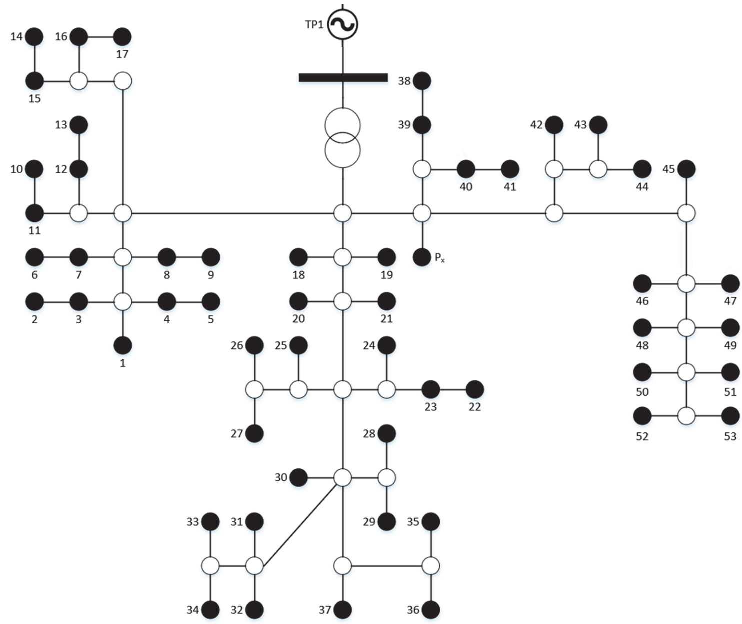

Figure 4. Topology of the LEC power system used in the case study.

Based on the collected data, a set of control and state variables is synthesised for each consumer and prosumer node. A summary of the connection capacity and available flexibility for each node is provided in Table 2. We use a simplified approach to incorporate power system flexibility. The following estimations and simplifications are applied:

- Each prosumer node is characterised by the amount of flexibility it has available (Table 2), which should be treated as synthesized sample values;
- Since the timestep of the simulation is 1 h, the flexibility is described as available energy;
- Each prosumer can provide up or down-regulation with a duration of 1 h;
- For up-regulation (decreasing output energy), for each prosumer, the rebound is considered with a duration of 2 h, during which a total of 30% more energy is consumed than what was used for flexibility activation;
- For down-regulation (increasing output energy), for each prosumer, the rebound is considered with a duration of 2 h, during which a total of 30% less energy is consumed than what was used for flexibility activation;
- Flexibility activation in both directions is always available for each prosumer, except during rebound.

A more accurate presentation of prosumer flexibility and its activation, including data about actual system requirements for purchasing flexibility, is in the scope of future research. For the utilisation of flexibility, a set of state space variables was generated, which is used to indicate how much of the magnitude can be utilised for each specific time-space. The control variables remain the same throughout all studied scenarios.

Mixed-integer linear programming (MILP) is used to evaluate the different scenarios. For the six scenarios, a deterministic setup is created using a one-year segment of the input data, PV production data for the year 2018 acquired from the EU Science Hub using the PVGIS Online tool [33] and Nord Pool Spot Market prices for years 2021 and 2022 [34].

The simulations aim to evaluate the differences between the potential of LECs that operate with different business logic and utilise different methods for asset dispatch. Six key indicators are used to assess LEC performance: self-consumption, self-sufficiency, levelized cost of energy (LCOE), import cost, export revenue and revenue from monetising available power system flexibility.

Table 2. A general summary of control and state variables for LEC nodes used in the case study.

Node	Connection Capacity (kW)	Flexibility (kWh)	Node	Connection Capacity (kW)	Flexibility (kWh)	Node	Connection Capacity (kW)	Flexibility (kWh)
1	11	0.2	19	11.0	0.2	37	11.0	1.3
2	11	0.0	20	21.0	1.8	38	13.0	0.0
3	11	0.6	21	11.0	0.8	39	13.0	0.8
4	11	0.0	22	11.0	0.5	40	13.0	1.3
5	11	0.0	23	11.0	0.2	41	11.0	0.5
6	11	0.0	24	11.0	0.0	42	11.0	0.5
7	11	0.0	25	13.0	0.0	43	21.0	1.3
8	11	0.2	26	11.0	0.2	44	11.0	1.1
9	11	0.2	27	11.0	0.5	45	26.0	4.5
10	16	1.6	28	16.0	2.5	46	11.0	0.0
11	16	0.6	29	16.0	1.6	47	11.0	0.5
12	11	0.0	30	11.0	0.2	48	11.0	0.0
13	11	0.2	31	11.0	0.2	49	11.0	1.3
14	16	0.5	32	11.0	0.0	50	11.0	0.5
15	16	0.8	33	11.0	0.6	51	11.0	0.8
16	16	4.5	34	11.0	0.0	52	13.0	0.0
17	16	3.1	35	11.0	0.5	53	13.0	0.8
18	16	1.6	36	11.0	0.6	Px	75.0	160.0

The self-consumption, denoted as SC, is calculated by Equation (3) as the ratio of PV generation used on-site to the total PV production.

$$SC = \frac{\sum produced\ PV\ energy - \sum exported\ pv\ energy}{\sum produced\ PV\ energy}. \tag{3}$$

The self-sufficiency of the LEC, denoted as SS, is considered as the share of prosumer demand, which is covered by on-site generation and is calculated using Equation (4).

$$SS = \frac{\sum E_{prosumer} - \sum E_{PCC,imp}}{\sum E_{prosumer}}. \tag{4}$$

In a general form, the LCOE can be defined as:

$$LCOE = \frac{sum\ of\ costs\ over\ lifetime}{sum\ of\ energy\ produced\ over\ lifetime,} \tag{5}$$

but this definition is typically applied to generation units only. In the concept of this work, the focus is on the LCOE for an entire LEC, which means Equation (5) is adapted separately for each investigated scenario. A detailed description of the calculation of the LCOE is provided with the description of each scenario. The cost of importing energy is calculated by Equation (6).

$$C_{import} = E_{Pcc,imp} \cdot (p_e + tariff), \tag{6}$$

where $E_{Pcc,imp}$ denotes the energy imported through the PCC, p_e is the price of energy at the Nord Pool Spot Market and $tariff$ the summarised capacity-based value for system operator tariffs and taxes specific to the environment. Nord Pool Spot Market prices for the year 2021 for Estonia (EE) market region are used. The case study uses a simplified approach for considering grid tariffs and relevant taxes, where a constant value of 0.025 €/kWh is used throughout the study. The energy export revenue is considered a negative cost and is calculated using Equation (7).

$$C_{export} = E_{Pcc,exp} \cdot p_e, \tag{7}$$

where $E_{Pcc,exp}$ denotes the energy exported through the PCC. Based on the existing tariff structure of Estonia, energy export is not taxed with grid tariffs and respective taxes. We use a simplified approach for assessing the value generated through flexibility incentives to manage the complexity of this work. We have purposely simplified the commonly applied method for incentivising flexibility, where the generated revenue comprises two components: separate remuneration for availability and activation. This study calculates the revenue generated through flexibility incentives using Equation (8).

$$C_{prosmer,flex} = p_{flex} \cdot E_{prosumer,flex}, \tag{8}$$

where p_{flex} denotes the price of flexibility activation and $E_{prosumer,flex}$ the energy used for flexibility activation. We have neglected input data about actual flexibility activations from the grid, and in this study, we use a simplified notion that the grid is willing to purchase flexibility activation at each time step. Improving the modelling of flexibility remuneration and considering actual activations is the subject of future work. Following is a detailed description of each scenario.

4. Modelling and Simulation of Optimisation Scenarios

The following subsections present the formulation of the optimisation problems. Let the set of time horizons be $\mathcal{H} = \{1, 2, \dots H\}$, where H is the length of the optimisation horizon and t the index of the time step. Let the set of prosumers be $\wp = \{1, 2, \dots, 53\}$, where the index of a prosumer is j. To manage computational requirements, the optimisation is performed with a 1-week time horizon, and all weeks of the year are simulated sequentially, with the results of the previous weeks used as input for the subsequent simulations. Optimisations for scenarios 1 to 5 are performed in this manner. The last, 6th scenario uses a 1-day horizon, and all scenarios utilise a 1h timestep.

4.1. Benchmark Scenario

A rule-based controller for the PV and BESS of P_x was developed to provide a comparative benchmark. The operational algorithm for controlling the BESS in the benchmark scenario is presented in Figure A1 (Appendix B). The control of the BESS in the benchmark scenario is based on energy flows through the PCC and the BESS's state of charge (SOC). The control is implemented such that the BESS aims to maximise self consumption. If the local generation produces more energy than is consumed by the LEC loads, excess energy is stored in the BESS until the SOC reaches 100%, upon which the excess energy is exported to the grid. However, if the local generation is not sufficient to cover LEC demand, the BESS is discharged to cover the deficit until the SOC drops to 20%, upon which the deficit is covered by importing energy from the grid. The equations below are used to determine the SOC of the BESS:

$$E_{BESS}(t) = E_{BESS}(t-1) + \mu_c E_{BESS,c}(t) - \frac{E_{BESS,d}(t)}{\mu_d}, \tag{9}$$

$$\mathrm{SOC}(t) = \frac{E_{BESS}(t)}{E_{BESS,max}}, \tag{10}$$

where E_{BESS} denotes the energy stored in the battery, $E_{BESS,c}$ the energy consumed by the BESS during charging, $E_{BESS,c}$ the energy produced by the BESS during discharging, μ_c charging efficiency and μ_d the discharging efficiency; SOC denotes the battery state of charge and $E_{BESS,max}$ describes the nominal capacity of the battery. The developed algorithm is designed to prohibit energy arbitrage by the BESS, and only excess PV energy can be exported through the PCC to the grid. Thus, Equation (3) can be reformulated as:

$$SC = \frac{\sum E_{PV}(t) - \sum E_{Pcc,exp}(t)}{\sum E_{PV}(t)}. \tag{11}$$

The LCOE for the benchmark scenario is calculated using Equation (12).

$$\text{LCOE} = \frac{C_{inv} + C_{maint} + C_{import} - C_{export}}{\sum P_{prosumer}}, \quad (12)$$

where, C_{inv}, C_{maint}, stand for the cost of investment and maintenance of the PV and BESS systems, respectively. The PV's investment cost is 556.99 €/kWp with a maintenance cost of 5.57 €/kWp per year [15]. The investment cost of the BESS is 1876.00 €/kW + 469.00 €/kWh, with a maintenance cost of 10.00 €/kW per year [13].

The results of the benchmark scenario indicate that the LEC has a high self-consumption rate of 92.9%. The self-sufficiency of the LEC was 25.2%, while the LCOE was calculated to be 0.134 €/kWh. The accumulated cost of importing energy for one year was 51,404 €, and the revenue from selling energy to the grid was 640 €. The total operation cost (the import less the export and flexibility revenues) was 50,764 € for the simulation period (1 year). To compare the performance of different scenarios, the results of all simulations are compiled in Table 3.

Table 3. Summary of simulation results with 2021 Nord Pool Spot Prices.

Parameter	Benchmark	EC+LSC	EC+MLC	PC+P2P	PC+LSC	PC+MLC	CFA+MLC
Self-consumption [%]	92.86	92.77	92.02	92.77	92.87	91.03	85.35
Self-sufficiency [%]	25.20	25.01	24.79	28.25	25.18	25.23	24.10
LCOE [€/kWh]	0.1338	0.1338	0.1329	0.1278	0.1328	0.1307	0.1192
Import cost [€]	51,404	51,478	51,165	51,522	51,082	48,665	47,085
Export revenue [€]	640	691	902	690	686	1043	2941
Flexibility revenue [€]	-	-	-	-	466	581	3682
Total operation cost [€]	50,764	50,787	50,263	50,832	49,930	47,041	40,462

4.2. Scenario 1: LEC as Energy Cooperative to Maximise Self-Consumption (EC+LSC)

In this scenario, the LEC is formed as an Energy Cooperative, where all 53 prosumers are equal members, and the assets of P_x are treated as community owned, where all profits and losses are shared among community members. The goal of the LEC is to maximise self-consumption, while the power output of the BESS is the only manipulated variable.

For this scenario, the optimisation variables include the charging and discharging energies of the BESS ($E_{BESS,c}$ and $E_{BESS,d}$), the energy output of the BESS (E_{BESS}), and the imported and exported energy through the PCC ($E_{Pcc,imp}$ and $E_{Pcc,exp}$). The maximisation of self-consumption of the LEC can be defined as maximising the share of locally produced energy that is consumed locally. In scenario 1, only the energy produced by the local PV systems can be exported. Thus the objective function can be formulated as to minimise the exported energy:

$$\min E_{Pcc,\text{exp}} = \sum_{t=1}^{H} E_{Pcc,exp}(t). \quad (13)$$

The optimisation task in this scenario is subject to different constraints. The defined BESS has a capacity of 200 kWh, with a minimum SOC value of 20%.

$$40 \text{ kWh} \leq SoC_{BESS}(t) \leq 200 \text{ kWh}. \quad (14)$$

The energy state evolution of the BESS can be described by an equality constraint Equation (15). The BESS is assumed to start the first timestep in a depleted state of 20% SOC.

$$\text{SOC}_{BESS}(t) = \text{SOC}_{BESS}(t-1) + E_{BESS,c}(t) \cdot \mu_c - \frac{E_{BESS,d}(t)}{\mu_d}. \quad (15)$$

The charging power of the BESS is limited by inequality constraints Equation (16), Equations (17) and (18), where $E_{BESS,c,max}$ and $E_{BESS,d,max}$ denote the maximum allowed charging and discharging power of the BESS (75 kW), which is considered the maximum amount of energy the BESS can absorb or release in 1 h. Additional auxiliary binary variables ζ_c and ζ_d are introduced to forbid simultaneous charging and discharging.

$$0 \leq E_{BESS,c} \leq E_{BESS,c,max} \cdot \zeta_c, \tag{16}$$

$$0 \leq E_{BESS,d} \leq E_{BESS,d,max} \cdot \zeta_d, \tag{17}$$

$$\zeta_c + \zeta_d \leq 1, \tag{18}$$

Even though the throughput limit of the PCC is not considered in this work, the constraints Equations (19)–(21) were implemented to forbid the simultaneous import and export through the PCC using auxiliary binary variables ζ_{in} and ζ_{out}. A large constant of 10 MWh was used as an energy limit.

$$0 \leq E_{Pcc,imp} \leq 10,000 \cdot \zeta_{in}, \tag{19}$$

$$0 \leq E_{Pcc,exp} \leq 10,000 \cdot \zeta_{out}, \tag{20}$$

$$\zeta_{in} + \zeta_{out} \leq 1, \tag{21}$$

In this scenario, the idea was to entirely utilise the locally produced PV power. Thus additional constraints Equations (22) and (23) were implemented to forbid energy arbitrage through charging and discharging the BESS from and to the grid.

$$\zeta_d + \zeta_{out} \leq 1, \tag{22}$$

$$\zeta_c + \zeta_{in} \leq 1, \tag{23}$$

An energy balance constraint Equation (24) was included to ensure that there would be a balance between the produced/imported energy and consumed/exported energy. The demand of prosumers is denoted with $E_{prosumer}$ and the combined PV production of grid-scale PV and the prosumer PV-s is given with E_{PV}.

$$E_{Pcc,exp} + E_{BESS,c} + E_{prosumer} = E_{Pcc,imp} + E_{BESS,d} + E_{PV}, \tag{24}$$

The LCOE for this scenario is calculated using Equation (12), the same as for the benchmark scenario. The results of the EC+LSC scenario show that maximising the self-consumption resulted in 92.8% of PV energy being consumed locally (self-consumption), while the self-sufficiency of the LEC was 25.0%. The levelized cost of energy was 0.134 €/kWh, while the accumulated cost for importing energy for one year was 51,478 €, revenue from selling to the grid 691 €, and total operation cost 50,787 €.

4.3. Scenario 2: LEC as Energy Cooperative to Minimise Levelized Cost of Energy (EC+MLC)

The second scenario uses the same Energy Cooperative business model utilised in the EC+LSC scenario but minimises the LCOE. Like the previous scenario, the only manipulated variable is the power output of the BESS, but the optimisation includes a price component. The algorithm attempts to shift the discharging of the battery to times of high electricity price to lower the cost of consumed energy. The optimisation variables and constraints remain the same as used in the EC+LSC scenario, while the optimisation objective is subject to change. The LCOE for this scenario is calculated using Equation (12), the same as for the benchmark scenario. The only influenceable parts of the LCOE equation are energy import and export cost components. Therefore, the optimisation objective of this scenario can be formulated as Equation (25).

$$\min \text{LCOE} = \sum_{t=1}^{H} C_{import}(t) - C_{export}(t) \tag{25}$$

where C_{import} denotes the cost of imported energy and C_{export} the revenue of exported energy (presented as negative cost).

The results of the EC+MLC scenario show that the maximisation of LCOE resulted in 92.0% self-consumption and 24.8% self-sufficiency. The LCOE of the LEC was 0.133 €/kWh, while the accumulated cost for importing energy for one year was 51,165 €, the revenue from PV energy export 902 €, and the total operation cost 50,832 €.

4.4. Scenario 3: LEC as Prosumer Community to Facilitate Peer-to-Peer Trading (PC+P2P)

The third scenario uses peer-to-peer (P2P) trading in a prosumer community. The LEC comprises 54 prosumers (all 53 prosumer nodes and the node denoted as P_x), which have formed a community to facilitate intra-community P2P trading. All prosumers are assumed to act selfishly to meet their individual goals. In this scenario, the demand flexibility of prosumers and consumers is also considered. The flexibility is monetised through an abstract aggregator which resides outside of the LEC and remunerates flexibility activation with a constant p_{flex} value of 0.01 €/kWh. The objective in this scenario is to maximise the matched energy production with consumption within the LEC. This objective is based on the hypothesis that matching energy inside the LEC increases economic feasibility since energy import is reduced. Thus, the cost of grid tariff is lower.

Additional optimisation variables need to be incorporated into the optimisation due to the inclusion of prosumer flexibility. The flexibility-aware prosumer load is denoted as $E_{prosumer,flex}$. The prosumer flexibility activations are considered with a binary variable $Pros_{flex}$. Two binary variables are declared to represent the state of rebound for each of the rebound hours, $Rebound_1$ and $Rebound_2$. Additional constraints need to be included in the addition of prosumer flexibility. The flexibility and rebound aware load of prosumers can be formulated with Equation (26).

$$\begin{gathered} E_{prosumer,flex}(j,t) = E_{prosumer}(j,t) + E_{Flex}(j) \cdot Pros_{flex}(j,t) - E_{rebound}(j) \cdot \\ Rebound_1(j,t) - E_{rebound}(j) \cdot Rebound_2(j,t), \end{gathered} \tag{26}$$

where $E_{Flex}(j)$ and $E_{rebound}(j)$ are the energies of activated flexibility and their subsequent rebound (as shown in Table 2 and described in Section 3). To prevent the activation of flexibility from resulting in negative demand for the prosumers, the following constraint is included:

$$E_{prosumer,flex}(j,t) \geq 0, \tag{27}$$

The rebound activation must happen directly in the subsequent timesteps of the flexibility activation. Therefore constraints Equations (28) and (29) are included. It is assumed that there is no rebound event in the first 2 h of the simulation year.

$$Rebound_1(j,t+1) = Pros_{flex}(j,t), \tag{28}$$

$$Rebound_2(j,t+1) = Pros_{flex}(j,t), \tag{29}$$

Due to the nature of a weekly optimisation horizon, it is assumed that the flexibility cannot be activated during the last 2 h of each week. This is because the optimisation algorithm is unaware of the demand of prosumers and the PV production of next week. Therefore, activating flexibility on the final 2 timesteps could result in an unfeasible solution for the next week. Flexibility activation during the rebound process is prevented with constraints Equations (30) and (31).

$$-1 \leq Pros_{flex}(j,t) + Rebound_1(j,t) \leq 1, \tag{30}$$

$$-1 \leq Pros_{flex}(j,t) + Rebound_2(j,t) \leq 1, \tag{31}$$

The energy balance constraint used in previous scenarios was modified to include the flexibility and rebound-aware prosumer load. The resulting constraint is formulated by Equation (32).

$$E_{Pcc,exp} + E_{BESS,c} + E_{prosumer,flex} = E_{Pcc,imp} + E_{BESS,d} + E_{PV}, \tag{32}$$

In P2P trading, the goal is to maximise the matched energy production and consumption within the LEC. This is implemented using Equation (33), where the optimisation goal is to minimise the absolute difference between imported and exported energy through the PCC.

$$\min E_{Pcc,dif} = (\textstyle\sum_{t=1}^{H} |E_{Pcc,imp}(t) + E_{Pcc,exp}(t)|), \tag{33}$$

The LCOE for this scenario is calculated using Equation (12), the same as for the benchmark scenario. The results of the PC+P2P scenario show that maximising the self-consumption resulted in self-consumption of 92.8% and self-sufficiency of 28.3%. The LCOE energy was 0.128 €/kWh, while the accumulated cost for importing energy for one year was 51,522 €, the revenue from selling to the grid 690 €, and the total operation cost 50,832 €.

4.5. Scenario 4: LEC as Prosumer Community to Maximise Self-Consumption (PC+LSC)

Like the EC+LSC scenario, this scenario aims to maximise the LEC's self-consumption, using the Prosumer Community business model described in the PC+P2P scenario. Since prosumers are assumed to act selfishly, they all attempt to maximise their individual self-consumption. The prosumers do this by timing their consumption to coincide with the period when PV is produced though their energy flexibility. The energy flexibility of consumers is not considered since they have no on-site generation to shift their demand. The prosumer P_x is considered different and aims to maximise the self-consumption of the entire LEC.

The simulation is performed in two steps: first, the operation of every prosumer is optimised individually; second, the operation of P_x is optimised using the results from the first step. For the second step, the optimisation variables and constraints remain the same as for the PC+P2P scenario. For the first step, the only difference is the energy balance constraint Equation (34), which does not include the BESS component.

$$E_{Pcc,exp} + E_{prosumer,flex} = E_{Pcc,imp} + E_{PV,prosumer}. \tag{34}$$

The optimisation goal Equation (35) remains the same as for the EC+LSC scenario, which also aims to maximise LEC self-consumption. However, it is used separately for each prosumer.

$$\min E_{Prosumer,exp} = \textstyle\sum_{t=1}^{H} E_{Pcc,exp}(t). \tag{35}$$

The calculation of the LCOE for comparing LEC performance includes the flexibility component Equation (8), which incentivises prosumers to use their flexibility.

$$\text{LCOE} = \frac{C_{inv} + C_{maint} + C_{import} - C_{flex} - C_{export}}{\sum E_{prosumer}}, \tag{36}$$

The results of the EC+LSC scenario show that maximising the self-consumption in a Prosumer Community resulted in self-consumption of 92.9% and self-sufficiency of 25.2%. The LCOE energy was 0.133 €/kWh, while the accumulated cost for importing energy for one year was 51,082 €, and the revenue from selling to the grid was 686 €. The revenue generated by providing flexibility was 466 €, and the total operation cost was 49,930 €.

4.6. Scenario 5: LEC as Prosumer Community to Minimise Levelized Cost of Energy (PC+MLC)

This scenario is like the EC+MLC scenario that attempts to minimise the LCOE of the LEC. However, in this scenario, the optimisation is carried out for a Prosumer Community described in the PC+P2P scenario. For this case, the prosumers are assumed to minimise their individual LCOE. Like the EC+LSC scenario, the optimisation is performed in two steps: first, for the 53 prosumer nodes, and second, for the prosumer P_x. Compared to the EC+LSC scenario, new optimisation variables are included that describe the flexible energy of the prosumers: $E_{prosumer,flex,up}$ and $E_{prosumer,flex,down}$. The objective function Equation (37) is extended from the EC+MLC scenario to include the component of revenue generated from flexibility Equation (38), and it is applied to individual prosumers.

$$\min \mathrm{LCOE}_{Prosumer} = \sum_{t=1}^{H} C_{import}(t) - C_{export}(t) - C_{prosumer,flex} \tag{37}$$

$$C_{prosumer,flex} = E_{prosumer,flex,down} \cdot p_{flex} - E_{prosumer,flex,up} \cdot p_{flex}, \tag{38}$$

The goal of the prosumer P_x is still to minimise the LCOE of the entire LEC using the objective function Equation (25) described in the EC+MLC scenario.

The results of the PC+MLC scenario show that minimising the LCOE in a Prosumer Community resulted in self-consumption of 91.0% and self-sufficiency of 25.2%. The LCOE energy was 0.131 €/kWh, while the accumulated cost for importing energy for one year was 48,665 €, and the revenue from selling to the grid was 1043 €. The revenue generated by providing flexibility was 581 €, and the total operation cost was 47,041 €.

4.7. Scenario 6: LEC as Collective Flexibility Aggregation to Minimise Levelized Cost of Energy (CFA+MLC)

The final scenario considers a LEC which operates under a Collective Flexibility Aggregation business model. In this scenario, the flexibility of the 53 prosumer nodes and the prosumer P_x is controlled by an aggregator, which resides inside the LEC. We consider a hypothetical setup where the DSO procures flexibility (up- and downregulation) with a step of 100 kW in 1 h blocks. To paraphrase it, the LEC operates as an aggregator and provides flexibility directly to the DSO. The activation of flexibility is rewarded with a constant p_{flex} value of 0.02 €/kWh. The remuneration of flexibility is double than considered in the PC+LSC and PC+MLC scenarios since there is no aggregator between the LEC and the system operator. The LEC aims to minimise its LCOE. Due to the computational requirements of this scenario, the optimisations are performed within a 1-day time horizon.

The previously used optimisation variables for prosumers were decoupled to represent the direction of energy flow: $pros_{flex,up}$, $pros_{flex,down}$, $rebound_{1,up}$, $rebound_{2,up}$, $rebound_{1,down}$, and $rebound_{2,down}$. Additionally, new optimisation variables were included in determining the binary activation of aggregated flexibility ($AGG_{flex,up}$ and $AGG_{flex,down}$) and the rebound of aggregated flexibility ($AGG_{reb,up,1}$, $AGG_{reb,up,2}$, $AGG_{reb,down,1}$ and $AGG_{reb,down,2}$). The energy of the BESS of P_x was decoupled into energy used during the period when no flexibility was activated ($E_{BESS,c}$ and $E_{BESS,d}$) and the period when flexibility was used ($E_{BESS,flex,c}$ and $E_{BESS,flex,d}$). The energy of aggregated flexibility was denoted as ($AGG_{flex,pwr,up}$ and $AGG_{flex,pwr,down}$).

Additional constraints Equations (39) and (40) were included for the aggregated control to ensure the flexibility of prosumers is only activated during aggregation.

$$pros_{flex,up}(j,t) \le AGG_{flex,up}(t) \tag{39}$$

$$pros_{flex,down}(j,t) \le AGG_{flex,down}(t) \tag{40}$$

The addition of constraints Equations (39) and (40) allows only a part of the prosumer portfolio to be activated if needed, so not all the prosumer flexibility has to be used simultaneously. To prevent the activation of aggregated energy flexibility during the rebound process, the constraints Equations (41)–(44) were included.

$$AGG_{flex,up} + AGG_{reb,down,1} \le 1 \tag{41}$$

$$AGG_{flex,up} + AGG_{reb,down,2} \leq 1 \quad (42)$$

$$AGG_{flex,down} + AGG_{reb,up,1} \leq 1 \quad (43)$$

$$AGG_{flex,down} + AGG_{reb,up,2} \leq 1 \quad (44)$$

The energy of aggregated flexibility was determined with equality constraints Equations (45) and (46).

$$AGG_{flex,pwr,up}(t) = E_{Flex}(j) \cdot pros_{flex,up}(j,t) + E_{BESS,flex,c}(t) \quad (45)$$

$$AGG_{flex,pwr,down}(t) = E_{Flex}(j) \cdot pros_{flex,down}(j,t) + E_{BESS,flex,d}(t) \quad (46)$$

In this scenario, the aggregated flexibility can only be activated with 100 kW steps, which provides the LEC only two options: up- or downregulation of 100 kW of aggregated flexibility. The constraints Equations (47) and (48) were introduced to implement this.

$$AGG_{flex,pwr,up} = AGG_{flex,up} \cdot 100 \text{ kW} \quad (47)$$

$$AGG_{flex,pwr,down} = AGG_{flex,down} \cdot 100 \text{ kW} \quad (48)$$

Due to the nature of the optimisation horizon of 1 day, it was necessary to prohibit the activation of aggregated flexibility during the 23rd and 24th hour of each day since the optimisation algorithm is not aware of the feasibility of the rebound effect at the beginning of the next day. Thus, $AGG_{flex,up}(23) = 0$, $AGG_{flex,up}(24) = 0$, $AGG_{flex,down}(23) = 0$, and $AGG_{flex,down}(24) = 0$.

The energy balance constraint used in previous scenarios was modified to include the flexibility component of the BESS system and is formulated as Equation (49):

$$\begin{gathered} E_{Pcc,exp} + E_{BESS,c} + E_{BESS,flex,c} + E_{prosumer,flex} = \\ E_{Pcc,imp} + E_{BESS,d} + E_{BESS,flex,d} + E_{PV}. \end{gathered} \quad (49)$$

The goal of scenario 6 is to minimise the LCOE. Therefore the previously used LCOE minimisation objective is modified to include the fixed aggregated flexibility activation incentive Equation (50) and is formulated as Equation (51).

$$C_{AGG,flex}(t) = 0.02 \cdot AGG_{flex,pwr,down}(t) - 0.02 \cdot AGG_{flex,pwr,up}(t) \quad (50)$$

$$\min \text{LCOE} = \sum_{t=1}^{H} C_{import}(t) - C_{export}(t) + C_{AGG,flex}(t), \quad (51)$$

The results of the CFA+MLC scenario show that minimising the LCOE in a LEC that utilises a Flexibility Aggregation business model resulted in self-consumption of 85.4% and self-sufficiency of 24.1%. The LCOE energy was 0.119 €/kWh, while the accumulated cost for importing energy for one year was 47,085 € and the revenue from selling to the grid 2941 €. The revenue generated by providing flexibility was 3682 €, and the total operation cost was 40,462 €.

5. Discussion

For this study, six scenarios and a benchmark case were simulated to investigate a LEC's potential performance. The same LEC setup was used in each simulation, but the different business models and methods for asset dispatch in Table 1 were applied. To evaluate the performance of different scenarios, the simulation results are analysed using the indicators in Sections 3 and 4. The relative difference in the performance of simulated scenarios compared to the benchmark scenario is provided in Figure 5.

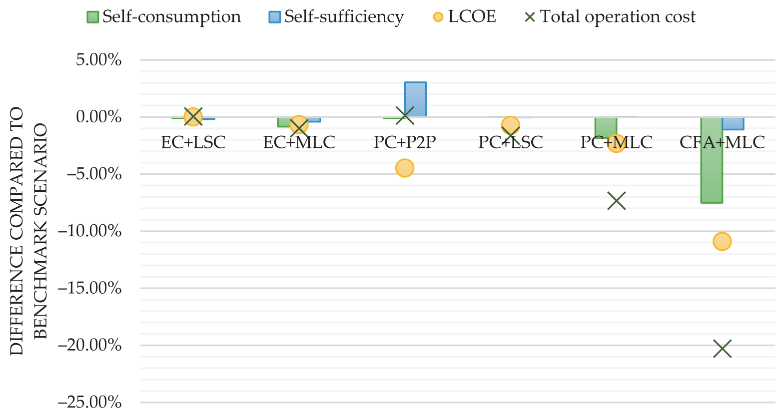

Figure 5. The relative difference in the performance of simulated scenarios compared to the benchmark scenario; self-consumption, self-sufficiency: higher is better; LCOE, total operation cost: lower is better.

The results of the benchmark scenario indicate that rule-based control of prosumer P_x provides considerably good results, as it provided the second highest self-consumption and third highest self-sufficiency rate compared to other scenarios while providing satisfactory economic performance. It can be concluded that if the sole aim of the LEC is to provide high levels of self-consumption, satisfactory results can be obtained using simple, rule-based control systems. Many state-of-the-art BESSs already provide an energy management system (EMS) to execute similar control as described in Figure A1, resulting in an inexpensive solution with relatively low computational requirements.

For the EC business model, insignificant differences exist between the simulation results of the maximisation of local self-consumption and the minimisation of LCOE. This is mainly due to the limited options for the LEC to influence its behaviour. Increased self-consumption also lowers the LCOE, which results in minimal differences between utilised asset dispatch methods.

An interesting observation is that the results of the EC+LSC scenario provided a lower self-consumption value than what was obtained for the benchmark scenario. This is caused by constraints Equations (22) and (23), which prohibit the BESS from charging and discharging to the grid. When simulating the EC+LSC scenario without these constraints, the resulting self-consumption reaches a value of 93.13 %, which would result in the highest self-consumption rate, but the number of BESS charge and discharge cycles would also increase significantly. We analysed the BESS charge and discharge operations for both cases (the charging and discharging to the grid allowed and prohibited) of the EC+LSC scenario. A summary of general properties describing the studied cases is provided in Table 4, while the BESS utilisation analysis is provided in Appendix B. When charging and discharging to the grid is prohibited, the number of cycles is reduced, while charge and discharge cycles are deeper. When charging and discharging to the grid is allowed, the number of cycles is increased by over 30%, and each cycle's depth is significantly lower than for the alternative case. The number of battery cycles affects their life cycle. Hence prohibiting the charge and discharge to the grid remained the preferred case in this study. We acknowledge that by modelling the impact of battery depletion into the optimisation algorithm, it would also consider the number of cycles and their depth of discharge. The improvement of the optimisation algorithm to consider the mentioned effects is the subject of future work.

Table 4. Analysis of BESS charging and discharging cycles during the EC+LSC scenario for the cases of charging and discharging to the grid prohibited and allowed.

Case Description	Charging and Discharging to Grid Allowed	Charging and Discharging to Grid Are Not Allowed
Nr of cycles	332	252
Charge Median [% of BESS capacity]	21.59	53.84
Charge Average [% of BESS capacity]	35.33	49.43
Discharge Median [% of BESS capacity]	17.86	52.38
Discharge Average [% of BESS capacity]	33.91	49.43

The simulation results for the PC business model have a higher variance than the EC. This indicates that for LECs operated as PCs, the significance of choosing the suitable asset dispatch method is higher than for LECs operated as ECs. One scenario that stands out is the PC+P2P, which produced the highest ratio of self-sufficiency and the best LCOE for the PC business model. The PC+P2P scenario provided a better LCOE than the PC+MLC scenario while having only 0.1% less self-consumption than the PC+LSC scenario. This can be explained by the nature of the simulation, where the optimisation algorithm aims to match energy production and consumption inside the LEC by utilising flexibility, which results in similar self-consumption rates and total operational cost as the benchmark scenario, but significantly higher self-sufficiency, which lowers the LCOE. Simulating the P2P asset dispatch with improved flexibility characterisation is a point of interest for future studies. Additionally, simulating and comparing operational P2P algorithms to the results obtained in this study are in the scope of future research.

When comparing the performance of the LSC asset dispatch method, the self-consumption values between the benchmark, EC+LSC and PC+LSC scenarios fall within 0.1%. The PC+LSC scenario produced the best values for LCOE and total operation cost, which can be accounted for by utilising flexibility. This indicates that different business models have an insignificant effect on maximising the self-consumption of the LEC.

The findings of the MLC asset dispatch method indicate, as predicted, that the use of power system flexibility has a considerable influence on the overall operating cost and the levelized cost of energy (LCOE). The lowest LCOE was achieved for the CFA+MLC scenario, where the LEC takes the role of the aggregator and provides grid services directly to the system operator. Since this work aimed to quantify the potential of different LEC business models and asset dispatch method combinations, the implementation and increased operation costs for the LEC to operate as an aggregator were neglected. The calculation of flexibility remuneration considering actual activations and providing detailed financial calculations for integrating and operating a virtual power plant by the LEC is the subject of future work.

The same simulations were run using 2022 Nord Pool Spot Market pricing to further investigate how the Spot Market affected the simulation findings. The respective benchmark and results of the simulations with 2022 Spot Prices are summarised in Table 5. The average energy prices on the Nord Pool Spot market in the EE price region were 0.087 €/kWh in 2021 and 0.192 €/kWh in 2022, corresponding to a price increase of 120.7%. Comparing benchmark values, self-consumption and self-sufficiency remain the same, while the LCOE increases by 49.5% and the total operation cost by 74.4%. Figure 6 displays the difference between the results of simulations that used 2021 and 2022 Nord Pool Spot market prices. The values displayed in Figure 6 are relative value differences, compared to respective benchmark values, between the results of simulations with different Nord Pool Spot market prices. As expected, the main differences are between LCOE and total operation cost, while the decrease is most notable for LECs utilising the MLC method for asset dispatch. For those LECs that utilise the MLC method for asset dispatch, it can be observed that the ratio of self-consumption is also decreasing. This means that under relatively high market prices, the LECs utilising the MLC asset dispatch method need to account for significantly reduced self-consumption.

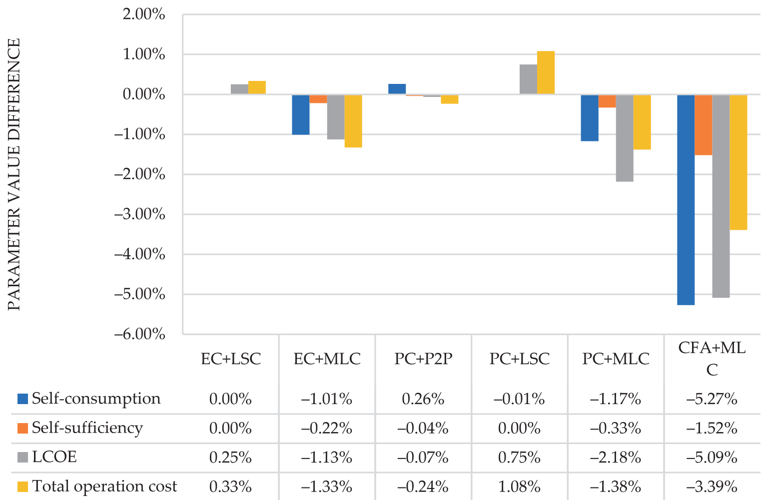

Figure 6. Differences between scenario simulation results (compared to benchmark) with different Nord Pool Spot market data. Simulation results with 2021 and 2022 Nord Pool Spot market prices are compared. Self-consumption, self-sufficiency: negative values show better performance with 2021 Nord Pool Spot market prices than with 2022 prices and vice versa; LCOE, Total operation cost: positive values show better performance with 2021 Nord Pool Spot market prices than with 2022 prices and vice versa.

Table 5. Summary of simulation results with 2022 Nord Pool Spot Prices.

Parameter	Benchmark	EC+LSC	EC+MLC	PC+P2P	PC+LSC	PC+MLC	CFA+MLC
Self-consumption [%]	92.86	92.77	91.01	93.03	92.86	89.86	80.08
Self-sufficiency [%]	25.20	25.01	24.57	28.21	25.18	24.90	22.58
LCOE [€/kWh]	0.2000	0.2005	0.1964	0.1909	0.2000	0.1910	0.1680
Import cost [€]	90,421	90,908	89,595	90,384	90,492	85,052	84,869
Export revenue [€]	1889	2 040	3112	1942	1991	3644	13,171
Flexibility revenue [€]	-	-	-	-	466	591	4136
Total operation cost [€]	88,532	88,868	86,483	88,442	88,035	80,817	67,562

Overall, it can be noted that the best PC+MLC and CFA+MLC scenarios give the best results from an economic point of view. However, the self-consumption and self-sufficiency are reduced in most cases. The PC+P2P and PC+LSC scenarios show lower improvements from the economic point of view, however, self-sufficiency and self-consumption never show significantly lower results compared to the benchmark case. Thus, the preferred combination depends on the overall goal for the LEC.

6. Conclusions

This study investigated the impact that different LEC business models and asset dispatch methods have on the performance potential of LECs. A benchmark and six scenarios were developed, modelled, and simulated using MILP. For each scenario, six key parameters were calculated and evaluated in order to estimate the prospective performance of the LECs and to benchmark their performance against other LECs. The key conclusions are stated below.

1. If the LEC aims to provide high levels of self-consumption, while there exists a limited number of controllable assets, simple, rule-based control systems provide a solution with low computational complexity that is easy to implement.
2. The utilisation of flexibility increases the LEC's economic performance, but different asset dispatch methods provide different rates of self-sufficiency.
3. When the LEC is utilising an energy cooperative business model, the selected asset dispatch method provides only minor differences in LEC performance.
4. For LECs operated as prosumer communities, the significance of choosing the suitable asset dispatch method is higher than those operating as energy cooperatives.
5. The LEC's business model has an insignificant effect on maximising its self-consumption.
6. For LECs operated as prosumer communities, the P2P asset dispatch method can provide a lower LCOE than other asset dispatch methods while realising that potential through operational P2P algorithms remains to be verified.
7. The LEC has the potential to significantly increase its economic performance by taking the role of the aggregator and directly providing grid services to system operators.
8. Increased energy prices reduce the self-consumption of the LECs that utilise the MLC asset dispatch method.

As a result of this work, we have quantified the potential of different LECs, the outcomes of this work will serve as a benchmark for evaluating the effectiveness of various operational optimisation and control techniques, which is the subject of future work. Secondly, the aim is to improve the presentation of prosumer flexibility availability and delivery, where data about power system flexibility requirements, activations and respective remuneration is included. The calculation of flexibility remuneration considering actual activations and providing detailed financial calculations for integrating and operating a virtual power plant by the LEC is the subject of future work, as well as simulating the P2P asset dispatch with improved flexibility characterisation. Another focus lies in improving the optimisation algorithm to consider the degradation of the battery based on BESS usage.

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Appendix A

A rule-based controller for controlling the BESS in the benchmark scenario is presented in Algorithm A1. If production exceeds consumption at the PCC, the BESS is charged until the SOC reaches 100%, upon which the excess energy is exported to the grid. If consumption exceeds production at the PCC, the BESS is discharged until the SOC reaches

20%, upon which the deficit is imported from the grid.

Algorithm A1: benchmark scenario

Input: $E_{prosumer}, E_{PV}, SOC$
Output: E_{BESS}, E_{Pcc}, SOC
if $E_{PV} > E_{prosumer}$ **then**
    if $SOC < 100$ **then**
        if $E_{PV} - P_{prosumer} > 75\ kW$ **then**
            $E_{BESS} = 75\ kW$
            $E_{Pcc} = E_{BESS} + E_{prosumer} - E_{PV}$
            calculate SOC
        else
            $E_{BESS} = E_{PV} - E_{prosumer}$
            $E_{Pcc} = 0$
            calculate SOC
        end
    else
        $E_{BESS} = 0$
        $E_{Pcc} = E_{prosumer} - E_{PV}$
        calculate SOC
    end
else
    if $SOC > 20$ **then**
        if $E_{prosumer} - E_{PV} > 75\ kW$ **then**
            $E_{BESS} = -75\ kW$
            $E_{Pcc} = E_{prosumer} + E_{BESS}$
            calculate SOC
        else
            $E_{BESS} = -(E_{prosumer} - E_{PV})$
            $E_{Pcc} = 0$
            calculate SOC
        end
    else
        $E_{BESS} = 0$
        $E_{Pcc} = E_{prosumer} - E_{PV}$
        calculate SOC
    end
end

Appendix B

A BESS utilisation analysis was carried out to evaluate the usage of the BESS with and without permission to use the grid for unlimited charging and discharging. In Figure A1, the BESS's capacity for each charging and discharging operation is depicted as a histogram. When no restrictions on using the grid apply, the BESS is used to perform cycles with lower capacities. Although battery manufacturers use the number of cycles to characterise battery lifetime, for some battery types, the impact of cycles on battery degradation is lower when these cycles are executed at higher SOC levels. To evaluate at which SOC levels the BESS is operated, the SOC at the end of each charge and discharge cycle is depicted in Figure A2. For both scenarios, the SOC of the battery is mostly around 20% at the end of the discharge cycles, which indicates that the battery of the BESS is operated mainly at the lower SOC levels.

It is concluded that applying the constraints for charging and discharging to the grid reduces the number of BESS cycles while the capacity of individual cycles increases.

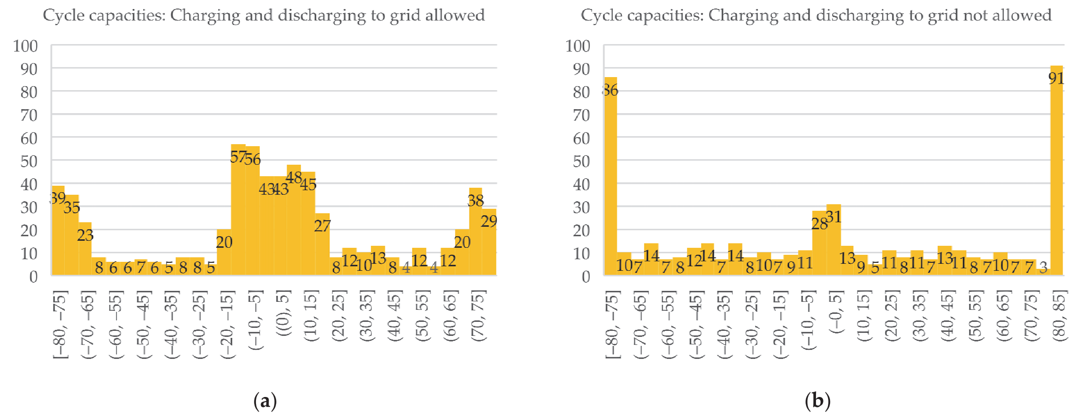

Figure A1. Comparison of BESS's capacity for each charging and discharging operation: (**a**) Charging and discharging to grid allowed; (**b**) Charging and discharging to grid not allowed.

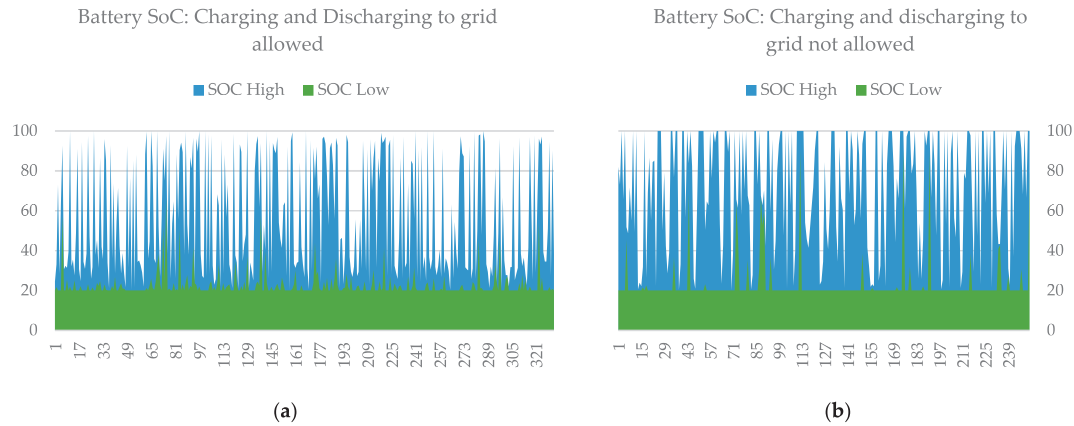

Figure A2. BESS SOC values at the end of each charge (SOC High) and discharge (SOC Low) cycle: (**a**) Charging and discharging to grid allowed; (**b**) Charging and discharging to grid not allowed.

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SURVEY

AI Technologies and Their Applications in Small-Scale Electric Power Systems

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ABSTRACT As the landscape of electric power systems is transforming towards decentralization, small-scale electric power systems have garnered increased attention. Meanwhile, the proliferation of artificial intelligence (AI) technologies has provided new opportunities for power system management. Thus, this review paper examines AI technology applications and their range of uses in small-scale electrical power systems. First, a brief overview of the evolution of small-scale electric power systems and the importance of AI integration is given. The background section explains the principles of small-scale electric power systems, including stand-alone systems, grid-interactive systems, microgrids, hybrid systems, and virtual power plants. A thorough analysis is conducted on the effects of AI technologies on power system aspects such as energy consumption, demand response, grid management, operation, energy generation, and storage. Based on this foundation, AI Acceleration Performance Indicators (AAPIs) for small-scale electric power systems are developed to establish a standardized framework for evaluating and comparing different studies. AAPI framework considers a binary scoring for five quantitative Key Performance Indicators (KPIs) and five qualitative KPIs examined through a three-tiered scale – established, evolved, and emerging.

INDEX TERMS Artificial intelligence, electric power systems, performance indicators.

I. INTRODUCTION

A. BRIEF OVERVIEW OF THE EVOLUTION OF SMALL-SCALE ELECTRIC POWER SYSTEMS

Significant developments in societal expectations, regulatory frameworks, and technology paradigms have shaped the evolution of small-scale electric power systems. Small-scale systems have historically served isolated locations or sectors, taking on a supporting role to centralized power grids. Due to technological breakthroughs, renewable energy sources have become more prevalent over time, and power generation equipment has become more affordable, propelling small-scale systems to become an essential component of modern-day sustainable energy solutions [1].

Decentralized energy production emerged in the early 20th century when small-scale systems used local resources like wind and water to produce electricity. These systems were distinguished by their independence from large-scale grids, and their location frequently served rural populations. There was a technological innovation boom in the late 20th century, especially in the area of renewable energy. Photovoltaic cells, wind turbines, and other clean energy technologies grew more efficient and affordable, as demonstrated by the increase in solar energy output from 30 GW to 118 GW and wind energy production from 78 GW to 167 GW within the European Union between 2010 and 2019 [2].

The need to switch to carbon-neutral energy sources has become more pressing due to growing worries about climate change and environmental pollution. As essential parts of the broader energy infrastructure, small-scale electric power systems are crucial in reducing the carbon footprint of conventional energy sources [3]. Nations all across the globe have pledged to cut greenhouse gas emissions and move toward sustainable energy practices under international

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agreements like the Paris Agreement [4]. Since small-scale electric power systems allow for localized, clean energy production with lower transmission losses, they provide a reasonable and practical solution to meet these global sustainability targets.

Although small-scale systems have evolved promisingly, there are still challenges, especially when incorporating fluctuating renewable energy sources. Advanced solutions like aggregated energy flexibility are required for efficient grid management because of the operational problems posed by the intermittent and variable nature of renewable energy sources like solar and wind [5]. In addition to benefiting the environment, small-scale electric power systems empower nearby communities by promoting energy independence, creating job opportunities, and boosting the local economy [6]. Decentralized energy resources in small-scale systems improve community sustainability overall and increase resilience to disruptions from the main grid.

B. IMPORTANCE OF INTEGRATING AI TECHNOLOGIES IN MODERN ENERGY SYSTEMS

The incorporation of artificial intelligence (AI) technology presents unique potential for enhancing the performance and reliability of small-scale electric power infrastructures. By employing machine learning, predictive maintenance algorithms can evaluate past data, identify patterns, and anticipate equipment breakdowns before they happen [7]. This lowers total maintenance costs by extending the lifespan of crucial components and minimizing downtime [8].

AI-powered load forecasting models make real-time energy demand forecasts possible, making grid management and resource allocation more effective [9]. These models improve the flexibility of small-scale systems by analyzing variables like user behavior, weather patterns, and past consumption data, guaranteeing that supply and demand are balanced [10]. Given that renewable energy sources are naturally uncertain, this capability becomes even more essential.

The introduction of AI-powered smart grid technologies is revolutionizing energy transmission, distribution, and usage. Fig. 1 demonstrates the components of small-scale power systems, which are the scope of this review paper. AI algorithms make real-time grid monitoring and control possible, allowing for automatic response to changing conditions. In addition to improving grid stability, it regulates fluctuations and keeps a steady supply of power, which facilitates the integration of various energy sources, including renewables [11].

AI plays a crucial role in coordination and control as small-scale electric power systems adopt increasingly decentralized energy resources. Decentralized energy management systems use AI to balance loads, optimize power flows, and coordinate the use of various energy sources. This raises the system's overall efficiency and strengthens the grid's resistance to disturbances [12].

Because renewable energy resources, such as wind and solar power, are unpredictable, sophisticated forecasting methods are required. To generate reliable renewable energy generation forecasts, AI algorithms analyze meteorological data, historical trends, and current conditions [13]. This makes it possible for grid operators to effectively incorporate renewable energy into small-scale power systems and manage fluctuations proactively.

For small-scale electric power systems to balance supply and demand, energy storage systems need to be optimized - AI technologies are key to this process. Optimizing energy storage devices' charging and discharging processes enhances their lifespan and efficiency, which is achieved via machine learning algorithms that analyze demand patterns, weather forecasts, and grid conditions [14].

Demand response programs powered by AI enable users to actively participate in energy-saving activities. These technologies help to increase overall energy efficiency and sustainability by allowing users to modify their energy consumption according to grid conditions through intelligent automation and real-time communication [15].

The paper is organized as follows: Section II provides background information on small-scale electric power systems. Section III is dedicated to an in-depth analysis of the existing literature related to AI applications in small-scale electric power systems. Section IV discusses the findings and proposes AI Acceleration Performance Indicators (AAIPs) that enable evaluating and comparing different studies. Section V concludes the review paper with relevant findings.

C. RELATED WORK AND MOTIVATION

The deployment of AI in power systems has become topical in the scientific literature as the number of publications related to deep learning and electric power systems in the ScienceDirect database has grown from around 20 in 2015 to 200 in 2019 [16]. Review articles related to this paper primarily focus on AI's applications in power systems [17], [18]. For example, the research status in the operation, optimization, control, dispatching, and management of Smart Grid and Energy Internet fields using AI has been reviewed in [19], where it was found that the bottlenecks for future development include the lack of training datasets, the interpretability and reliability of models, and semantic reasoning issues of language models. Machine learning algorithms, such as Support Vector Machines (SVMs) and Gradient Boosting Machines (GBMs), have been utilized to predict energy consumption patterns with high accuracy, enabling more efficient demand response and load forecasting [20], [21]. AI supports VPPs by optimizing the utilization of renewable resources based on their availability and demand predictions [22]. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated exceptional capability in identifying and diagnosing faults within microgrids, thus reducing downtime and maintenance costs [23], [24].

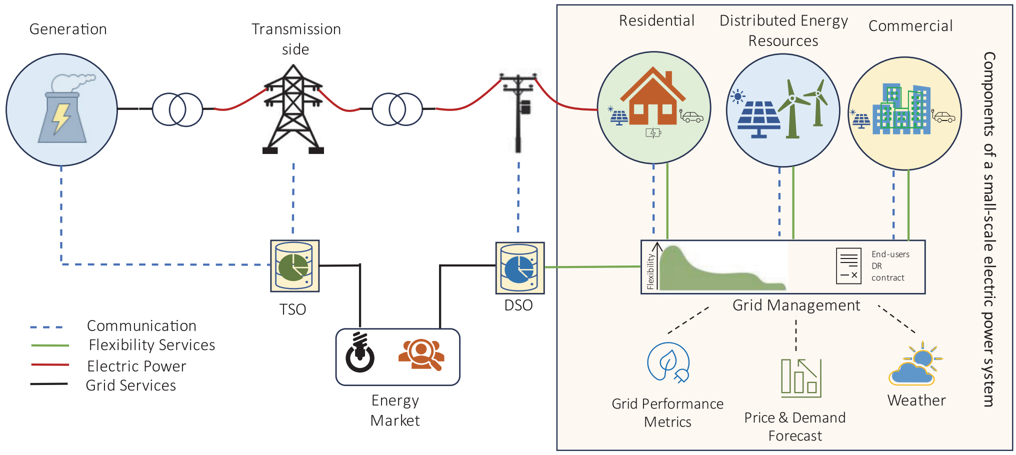

FIGURE 1. **Illustration of the structure of a power system.**

Furthermore, reinforcement learning approaches, including Deep Q-Networks (DQNs) and Proximal Policy Optimization (PPO), have been utilized to optimize microgrid operations and manage distributed energy resources more effectively, thereby enhancing overall system performance and sustainability [25], [26]. The authors of [27] reviewed Explainable Artificial Intelligence techniques for energy and power systems. The application of resilience enhancement of power systems using AI was reviewed by the authors of [28], who concluded that supervised deep learning is particularly suited for anomaly detection, classification, and damage detection. In contrast, unsupervised deep learning methods are suitable for defending against cyber-attacks. Thus, the research has primarily focused on AI applications in power systems; however, to the authors' best knowledge, there is a lack of research in evaluating and benchmarking the efficacy of AI implementations in electric power systems. Therefore, the motivation of this research paper is not only to give a comprehensive review of AI applications in small-scale electric power systems but also to provide a framework for evaluating and benchmarking the efficacy of AI implementations using the AAPI framework developed in this paper.

D. REVIEW METHODOLOGY

A thorough literature search was conducted across major academic databases such as Scopus, ScienceDirect, and IEEE Xplore. The search strategy included a combination of the following keywords and many more: "AI technologies," "small-scale electric power systems," "microgrids," "energy consumption," "demand response," "grid management," "energy generation," and "energy storage." The focus was on newer studies conducted from 2019 to 2024.

The inclusion criteria for selecting relevant studies include peer-reviewed journal articles and conference papers that specifically address the focus of this study, namely the impact of AI technologies in small-scale electric power systems. Studies that either provided insufficient information about the uses of AI technology or did not explore the relationship between AI and small-scale electric power networks were excluded from the analysis.

The key themes of the literature were identified through systematic data extraction. The data was compiled into tables based on which the objectives, methodologies, AI models, key findings, and limitations of existing research can be analyzed.

II. FUNDAMENTALS OF SMALL-SCALE ELECTRIC POWER SYSTEMS

The effective operation of small-scale electric power systems is essential in meeting the changing energy demands. The basic concepts of these systems, which include standalone, grid-interactive, microgrid, hybrid, and other configurations, including Virtual Power Plants (VPPs), are examined in this section.

A. STANDALONE SYSTEMS

Reliable electricity supply in isolated or off-grid places relies heavily on small-scale electric power systems, mainly standalone designs. These systems have become essential in addressing issues related to energy access because of their independence from the main grid [29]. Standalone systems include devices such as production units, energy storage, and loads. Energy is produced with diesel generators, combined heat and power units, or renewable energy sources like solar or wind. At the same time, the storage, which usually takes the form of batteries, guarantees a steady supply of electricity at times when production is low. Optimizing the performance of standalone systems requires understanding how these components interact [30].

Although standalone systems provide energy independence, they have maintenance, fuel supply, and reliability issues. Despite these challenges, standalone systems are viable for some applications due to their flexibility, autonomy, and lower environmental impact [31]. Examples from real life demonstrate the adaptability and efficiency of standalone systems [32]. Applications for standalone systems are diverse; they can be used to power distant communication stations or provide electricity in rural areas or areas affected by disasters. In situations when grid access is difficult or economically unreasonable, these systems showcase their importance in meeting energy demands [33].

B. GRID-INTERACTIVE SYSTEMS

Grid-interactive systems are a type of small-scale electric power systems that integrate with the main grid. By enabling bidirectional power flow, these systems allow an interchange of electricity between the main grid and the local power sources [34].

Integrating grid-interactive equipment with the main grid is a crucial component that makes a consistent and dependable power supply possible. Grid compatibility and control methods are subject to additional challenges in the context of bidirectional power flow, allowing electricity to be provided to and consumed from the grid [35].

Grid-interactive systems have several advantages, such as improved energy efficiency and higher reliability, thanks to grid assistance. However, for deployment to be effective, obstacles to maintaining grid stability and resolving regulatory concerns must be carefully considered [36].

C. MICROGRIDS

Microgrids represent a significant shift in small-scale electrical power systems, offering localized control and independence. Microgrids are characterized by having the ability to function both autonomously and alongside the main grid, i.e., in off-grid or on-grid modes. These attributes are among the major reasons for their increasing appeal. There are several use cases of microgrids, each designed to meet specific requirements, e.g., community, campus, and remote microgrids [37]. It is necessary to understand these distinctions to develop microgrids that meet the particular needs of various settings.

Microgrid management is greatly aided by advanced control systems, which ensure optimal performance and coordination between various energy sources. The responsiveness and flexibility of microgrid systems are improved by integrating intelligent technologies such as optimization and machine learning algorithms [38]. Enhancing power supply reliability is one of microgrids' distinguishing features. Microgrids play an important role in attaining energy security and contribute to grid stability by offering localized solutions to energy-related problems [39].

D. HYBRID SYSTEMS

Hybrid systems are a complex solution to small-scale electric power systems since they integrate multiple energy sources. These systems combine the benefits of many technologies by integrating renewable energy sources with conventional generators [40]. The viability and versatility of this technique are demonstrated by examples of hybrid systems, such as wind-hydro or solar-diesel combinations. Intermittency-related issues are resolved by combining renewable and conventional sources to ensure a more steady power output [41]. Other benefits include better environmental sustainability, decreased dependency on fossil fuels, and enhanced efficiency. However, the challenges in designing and integrating complex systems call for both careful planning and innovative technologies [42].

E. VIRTUAL POWER PLANTS

The concept of Virtual Power Plants (VPPs) is new in the world of small-scale electric power systems. These designs provide a scalable and adaptable solution by combining distributed energy resources through the use of modern technologies. Due to their ability to coordinate operations centrally, VPPs are essential for optimizing the usage of distributed resources [43]. Beyond conventional power generation, VPPs are also applicable for energy storage and demand-side control, which improves system efficiency as a whole [44]. Improved stability of the grid, effective resource use, and a lower carbon footprint are just a few of the economic and environmental advantages that come with the deployment of VPPs [45]. It is anticipated that as technology develops, VPPs will have an even more significant impact on small-scale electric power systems.

III. AI APPLICATIONS IN SMALL-SCALE ELECTRIC POWER SYSTEMS

Integrating Artificial Intelligence into small-scale electric power systems presents a promising opportunity for managing and optimizing energy resources distinct from those encountered in large-scale systems. While AI's applications in both contexts aim to enhance efficiency, reliability, and optimization, the scale of operation significantly influences the nature and impact of these applications.

In small-scale systems, the applications of AI range from enhancing the efficiency and reliability of distributed energy resources, such as through predictive maintenance, optimal segmentation of renewable sources, and accurate forecasting, to optimizing battery energy storage and consumption by predicting remaining useful life (RUL), SoC patterns, and charging and discharging times. AI in these settings is focused on enhancing local grid stability, managing dynamic load, and integrating a higher proportion of renewable energy sources. Due to the smaller scale, AI-driven strategies are more agile, tailored to local conditions, and responsive to rapid changes in demand and supply. It plays a pivotal role in intelligent load management and demand response, providing dynamic pricing strategies and balancing supply and demand while predicting consumer behavior for optimized energy distribution. Furthermore, AI significantly boosts small-scale grid management by enabling real-time anomaly detection, predictive maintenance, and dynamic reconfiguration in microgrids to enhance grid stability and resilience and maintain continuous and efficient power delivery.

On the other hand, AI applications in large-scale power systems typically deal with the complexity of interconnected networks and centralized generation facilities, focusing more on high-level grid management, large-scale energy trading, and maintaining the reliability and security of supply across vast geographical areas.

The scope of AI in small systems extends to sophisticated applications such as coordinating VPP and community energy systems, aggregating, and intelligently managing diverse energy resources. Following the overview, the subsequent sections will thoroughly discuss the specifics of each area, exploring the enhancement of energy generation, storage, consumption, grid management, and advanced applications within small-scale electric power systems through AI technologies.

A. ENERGY CONSUMPTION AND DEMAND RESPONSE

In the domain of small-scale electric power systems, the application of artificial intelligence in energy consumption and demand response offers model-free solutions as compared to traditional mathematical models to analyze consumption patterns, predict demand peaks, exploit consumer energy flexibility, and implement dynamic load adjustments, perform real-time pricing and offering innovative solutions for intelligent energy management at both household and building scales either with residential or community settings.

A DRL algorithm to schedule ESS and HVAC loads in a smart home without building thermal dynamics is proposed in [46]. The results indicate 8.10%–15.21% cost minimization compared to rule-based control approaches. In [47], the Temporal Convolutional Networks (TCNs) are utilized for community energy management using PV and ESS. Energy consumption optimization includes data-driven models for occupant behavior, user comfort, and RES management using Random Forest [48], NARX ANN [49], DNN [50], and Q-Learning [51]. Similarly, energy demand prediction for economic and energy savings is also a key aspect of DR strategies. In the literature, authors employed different machine-learning techniques for short-term [52], [53], [54] and day-ahead load forecasting [55], [56], [57] to enhance consumer engagement in energy trading, renewable energy integration, and dynamic tariff schemes. Table 1 comprehensively examines AI-driven strategies for enhancing energy consumption patterns and refining demand response mechanisms for small-scale electric power systems.

B. GRID MANAGEMENT AND OPERATIONS

Energy fluctuations from intermittent renewable energy generations introduce vulnerability in grid operations [69]. ML plays a crucial role in transforming grid management, particularly in enhancing the capabilities for on-grid system optimizations, dynamic reconfiguration in microgrids, and anomaly detection in power systems. For example, the LSTM-based reinforcement learning model improved renewable energy integration and load balancing optimization in a smart grid with 92% accuracy as compared to other ML algorithms [70]. On-grid system optimization involves interactions between various microgrid components such as consumers, renewable energy producers, electricity suppliers, and storage systems. This interaction is characterized by dynamic reconfiguration, adapting microgrid operations to varying factors like renewable energy production, consumption patterns, and storage capacities [71]. A techno-environmental-economic strategy using multi-agent DRL for microgrid planning and optimization is presented in [72]. Effective grid management requires improved prediction stability of microgrids. This includes load-shifting, demand offsetting, decision-making in virtual power plants, and providing ancillary services, thereby focusing on urban scales and their inherent complexities [73]. To ensure grid reliability and security, federated learning techniques allow for on-device model training and parameter updating, significantly enhancing privacy and reducing data transmission requirements. These approaches, secured with SSL/TLS protocols, effectively mitigate challenges related to bandwidth, latency, and security, aligning with stringent privacy regulations [74]. To provide security to client data in microgrids from being compromised, a CNN-BiLSTM categorization criterion for cyber-attacks has shown a success rate of 99% compared with traditional approaches [75]. Table 2 summarizes the research on AI applications in grid management and operations of small-scale electric power systems.

C. ENERGY GENERATION

Smart grid technology has enabled the potential benefits of RES for consumers in small-scale electric power systems. In this context, the application of AI becomes instrumental in enhancing energy generation capabilities by optimally positioning and controlling RES to maximize the efficiency of these installations, specifically for the task of maximum power point tracking (MPPT) and adaptive power management [76]. By analyzing historical data from various sensors, AI algorithms predict potential failures, remaining useful life (RUL), and schedule timely maintenance of equipment, thus minimizing downtime and extending the lifespan of the generation equipment. Furthermore, accurate solar irradiance and wind speed forecasts enable proper load scheduling and grid power allocation, ensuring a steady and reliable energy supply [77]. A SHAP cat-boost algorithm improves MPPT control in PV systems by minimizing steady-state error during low irradiance and partial shading conditions [78].

TABLE 1. Summary of AI studies for energy consumption and demand response.

Ref.	Objective	AI Technology	Data Source	Methodology	Scale	Key Findings	Limitations	Further Research
[58]	Efficient residential demand control	Deep Learning	German building dataset for PV and WWO API for weather data	rTPNN-FES algorithm for concurrent RES forecasting and appliance scheduling optimization	Household	Single algorithm provides near-optimal appliance scheduling 37.5 times faster than traditional methods	Lacks integration of thermal models with HVAC control systems	Application to microgrid dispatch and intelligent energy distribution
[59]	Manage energy demand by exploiting consumer flexibility for participation in energy trading	Deep Learning	MATLAB simulation data	LSTM for demand predictions and matrix-based control system to maximize RES consumption	Community	21% demand reduction during DR events, 15% reduced interaction with the electricity network	Only considers residential load	Integration with other renewable sources and wider geographical application
[60]	Analyze energy consumption patterns to enhance consumer engagement in energy markets	Unsupervised Learning, Data Mining	Five house data UK-Dale dataset	K-means clustering for appliance-time association and FP Growth for appliance-to-appliance association.	Household	Identification of Appliances of Interest for efficient demand management and end-user participation	Focuses on the frequency of appliance usage rather than their actual energy consumption or duration of use.	Predicting appliance usage on a short-term and long-term basis to analyze consumer preferences
[61]	Characterize the flexibility of residential electricity consumption for demand response	Interactive Learning (IL)	IRISE Energy dataset	NILM for disaggregation, Random Forest to estimate appliance ON-OFF events, and k-means for flexibility curves	Residential	High accuracy in characterizing flexible appliances using IL-based disaggregation	Limited to low-resolution smart-meter data	Integration of more diverse datasets, including EVs, solar PV, and batteries
[62]	Balance energy consumption and production in buildings to work as a local power plant	Machine Learning	DesignBuilder Simulation	By managing energy supply and demand using PV systems, XGBoost is used to predict future energy balance.	Urban Building Complex	Surplus energy generation from April to December for peak demand management	Accurate system modeling challenges, need for extensive data	Optimizing PV plant siting and operation to maximize profits
[63]	Improve Short-term Load Forecasting accuracy and privacy for residential users	Federated Learning	Australian SGSC customer dataset	K-means based privacy-preserving user clustering with a hierarchal federated ANN forecasting model to enhance fault tolerance	Residential	Compared with benchmark methods, 37.25% improvement in prediction accuracy	Vulnerable to eavesdropping attacks, does not account for social relationships in clustering	Expansion to diverse residential environments, Integration of encryption technologies for enhanced security
[64]	Optimize energy management through occupancy forecasting	Semi-supervised, Deep Reinforcement Learning	Real-world datasets from Belgium and Germany	LSTM integrated LTPWE for occupancy estimation integrated with SAC for energy scheduling	Residential and Commercial	Reduced energy cost by 18.79%–55.79% without sacrificing thermal comfort	Dependency on ambient data quality and labeling frequency	Optimization with varying environmental conditions
[65]	Optimize energy consumption and maximize user comfort	Transfer Learning	UK-DALE, REFIT datasets	Deep Q-learning is employed to transfer knowledge from the expert's	Household	Significant reduction in energy consumption with minimum user discomfort	Preprocessing and fine-tuning requirements in knowledge transfer	Use of graph neural networks for enhanced TL efficiency

TABLE 1. ***(Continued.)*** **Summary of AI studies for energy consumption and demand response.**

	in smart homes			home to the learner's home.				
[66]	Optimize energy consumption in the home energy management system	Deep Reinforcement Learning (DRL)	UK Power Networks and Nordpool database.	DRL is utilized in an MDP framework with a state set of appliances, EV, and ESS attributes, and a reward function	Household	Minimized electricity cost and reduced transformer load. Power peak cut of 24% in some instances	Black-box nature of DRL, high-dimensional state-action space	Interpretability and scalability of the DRL model
[67]	Designing DR programs for prosumers	Clustering Algorithms	Smart meter data from Italian utility	Utilized k-means, k-medoids, and agglomerative clustering to identify and optimize DR program for prosumers	Community	Effective DR segmentation minimized reverse power flow, a PPS of 0.689 for k-means	Low volume of data, limited to a specific community	Deployment as an application for aggregators, incorporating forecasts and dynamic DR strategies
[68]	Mitigate high rate of change of frequency in PV-operated grid systems	Deep Learning	Grid emulator data with PV systems, Malaysia	Development and testing of ANN-based DR controller for frequency regulation in high PV intermittency areas	University Campus	Reduced frequency deviation by 23%, improved ROCOF by 19.7%	Specific to conditions near the equatorial line, requires high-quality data	Expansion to different geographic and grid conditions

A Q-learning-based control strategy has identified optimal equilibrium policies for various power system operating conditions and improved control performance by around 10% compared to other ML algorithms [79]. Similarly, for predicting the RUL of rotating machines, a DNN-based model is utilized that considers time–frequency-wavelet joint features to effectively represent the degradation of bearings [80]. A deep learning-based RNN model is designed to forecast short-term intra-hour solar irradiance by using infrared sky images, resulting in reduced algorithm computational cost and grid operational cost with high participation of solar energy [81]. Table 3 provides a detailed overview of AI applications for optimizing energy generation in small-scale electric power systems.

D. ENERGY STORAGE

Efficient energy storage management is essential for the effectiveness and reliability of small-scale electric power systems that rely on intermittent renewable energy sources, such as solar and wind [101]. The development of energy storage system (ESS) technologies such as compressed air, flywheel, pumped hydro storage, and batteries can increase the ESS capacity to store energy from power grids. This stored energy can then be used when needed. The advancement of ESS technologies with microgrid utilization has created a large market for ESS to offer bulk energy storage, transmission and distribution support, ancillary services, and energy management solutions [102]. AI technologies significantly enhance the capabilities and functionalities of ESS by providing battery-based control and monitoring solutions, predicting battery health, optimizing charging cycles based on real-time energy demands, and identifying degradation patterns [103]. A predictive control mechanism has demonstrated an 84% overall efficiency in microgrid peak shaving by managing the flow rate of energy storage systems for stable power generation [104]. To improve the real-time charging/discharging decision-making of ESS, RL-based actor-critic agents are used to optimize the power flow while minimizing the energy cost [105]. Battery state of health is determined with a mean absolute error of 1.39% by using a simple ANN with a small amount of data. This helps optimize the operation and management of energy storage systems [106]. A degradation model of lithium batteries is developed to predict the remaining useful life using ensemble learning methods for fault diagnosis during the equipment operation service period to ensure an effective energy supply [107].

Table 4 analyzes AI-based techniques to improve the operation of energy storage systems in small-scale electric power systems.

IV. DISCUSSION

A. AI ACCELERATION PERFORMANCE INDICATORS (AAPIS) FOR SMALL-SCALE ELECTRIC POWER SYSTEMS

In the rapidly evolving field of small-scale electric power systems, the integration of AI has shown promising potential. However, a critical gap exists in the standardization of evaluating and comparing the diverse AI methodologies being employed for similar tasks. This requires a set of baseline assessment parameters to establish a standardized

TABLE 2. Summary of AI studies for grid management and operations.

Ref.	Objective	AI Model	Data Source	Methodology	Scale	Key Findings	Limitations	Further Research
[82]	Implementing efficient energy management in microgrids	Deep Reinforcement Learning	Data from Institut Polytechnique de Paris microgrid	Deep LSTM for time series prediction, ILP for optimal action calculation, and reinforcement learning for decision-making	Microgrid	DRL system achieves up to 95% accuracy compared to optimal actions, outperforming the Q-learning method	Complexity in model representation with ILP, long execution time of Q-learning	Further exploration of DRL in various use cases, including deployment on micro-controllers
[70]	Optimize renewable energy production in smart grids	Deep Learning, Reinforcement Learning	Smart Meter Power Consumption Data in London Households	LSTM-RL for demand patterns; RL-SA for load balancing; CNN-PSO for energy production forecasting	Smart Grid	LSTM-RL accuracy: 0.92; RL-SA load balancing accuracy: 0.91; CNN-PSO's RMSE: 18.57.	Reliance on precise input data, computational complexity in large-scale systems	Dynamic pricing and DR strategies, alternative optimization methods
[83]	Enhance Smart Grid security via theft detection	Federated Learning	US Open Energy Data Initiative (OEDI) portal	FL-ConvGRU decentralized model for theft detection by capturing spatial patterns and temporal dependencies	Smart Grid	High efficacy in detecting theft with data privacy at 0.980 accuracy, 0.970 Recall, 0.980 F1-Score	Complexity of the model and data synchronization	Hyperparameter optimization, alternative deep-learning architectures for improved theft detection
[84]	Simulate critical scenarios to optimize smart grid operation and flexibility	Deep Learning, Reinforcement Learning	European ebalance-plus project data	LSTM for prediction, DQN for optimizing multi-agent systems to achieve operational flexibility	DC Microgrid	Optimal actions were achieved with 90% accuracy in consumption patterns and NMAE of 0.72	System's non-scalability due to environmental requirements	Expand scalability with a more dynamic environment definition
[85]	Energy management in vehicular ad hoc networks (VANETs) using IoT and microgrids	Reinforcement Learning	VANET system data	Variational Encoder NN algorithm within an IoT-based edge cloud computing framework and integration with smart microgrid architecture	Microgrid	The model achieved 96% energy efficiency while reducing communication overhead by 55%	Security, privacy, interoperability in VANET-Cloud	Addressing VANET-Cloud challenges
[86]	Improve smart grid prediction stability to enhance system efficiency	Supervised Learning	UCI ML database	Cascade ML system with feature selection and FCMFW-Bagged Tree algorithm-based classification.	Smart Grid	Achieved 99.9% accuracy in predicting SG stability	Specific to the dataset used, may require adaptation for other SG systems	IoT-based E-stability determination systems
[87]	Identify and classify transient conditions in microgrid	Supervised Learning	MATLAB simulation of WBREDA and WBSEDCL distribution system	Signal processing through Discrete Wavelet Transform.	Microgrid	100% accuracy in detecting and discriminating transient events	Generalizability to different microgrid configurations or noise sensitivity.	Exploration of transient events and grid-connected hybrid network

TABLE 2. ***(Continued.)*** **Summary of AI studies for grid management and operations.**

				Training Decision Tree classifier using extracted features.				with nonlinear load
[88]	Optimize control strategies for multiple VPPs integrating EVs	Federated Deep Reinforcement Learning (FDRL)	VPP operation data, EV charging/discharging data	FDRL with a stochastically controlled stochastic gradient with Markov decision process formulation	Virtual Power Plant	Achieved the highest reward values at 3.85 × 10^5, indicating better VPP control strategies	Complexity in managing disturbances, data privacy concerns	Expansion of FDRL application to larger grid systems
[89]	Optimize VPP decision-making in urban areas	Reinforcement Learning	BRCET database	Utilized DDPG for optimal VPP control, addressing spatial/temporal uncertainties via scenario analysis	Urban VPP	Improved economic benefits via load-shifting, demand offset, and market participation	Simulation interval limits, electricity market bidding process not considered	Integrating RL with game theory for electricity market bidding, extending VPP modeling with RL
[90]	Optimize EV charging/discharging for V2G integration	Reinforcement Learning	KEPCO's EV charging data	Model-free sequential decision-making using MDP and DDPG algorithm	Smart Grid	Reduced user costs by 59%-62% and extended battery lifespan	Uncertainties in driving behavior and battery degradation	Inclusion of detailed user requirements, improving the DDPG algorithm,
[91]	Anomaly detection in smart grids	Federated Learning	Ausgrid, KDD 99, NSL-KDD, CIDDS datasets	Locally train global models (RNN, 1D-CNN, LSTM) while securely updating the central model via SSL/TLS	Smart Grid	FL-1D-CNN Classifier showed the highest 0.981 accuracy with 0.871 precision.	Limited by data and device heterogeneity	Optimizing FL for lower resource consumption on edge devices

framework that enables evaluating and comparing different studies. Considering the variations in methodologies and outcomes in energy sector research, the AI-Acceleration Performance Indicators (AAPIs) are proposed as an initial proposition to provide a consistent benchmark for AI-accelerated approaches. It involves identifying key performance indicators (KPIs) crucial for evaluating AI in small-scale electric power systems. The process is guided by the dual objectives of ensuring technological viability and enhancing user-centric outcomes. AAPI framework serves as a starting point for standardization in the field, with the main purpose of establishing a foundation upon which further research and validation can be built.

The accelerated KPIs are designed to speed up the commercialization of AI technologies in energy systems by ensuring user comfort, scalability, and practical applicability while enhancing user engagement. The framework categorizes KPIs into quantitative and qualitative measures, as outlined in Table 5.

Key performance areas critical to AI applications in energy systems are identified, such as cost-effectiveness, demand management, and prediction accuracy, along with qualitative aspects like innovation level and practical applicability. AAPIs framework employs a binary scoring system for quantitative KPIs to highlight which aspects are clearly covered in the studies. In contrast, the qualitative aspects are examined through a three-tiered scale – established, evolved, and emerging, where established indicator shows real-world, data-driven, and validated AI solutions with reliable results in different operating scenarios, evolving parameter shows the ongoing development and incremental improvements in the research with simulated analysis to enhance practical viability. In contrast, emerging shows new machine learning concepts and early-stage AI solutions that are yet to be extensively tested but point to new directions that could drive future advancements. This assessment approach guides the field towards practical, user-oriented, and commercially sustainable AI solutions.

These indicators are applicable across various types of AI applications, be they computational, experimental, or integrative. Researchers can track the evolution and performance enhancements of these systems by consistently

TABLE 3. **Summary of AI studies for optimizing energy generation for small-scale electric power systems.**

Ref.	Objective	AI Technology	Data Source	Methodology	Scale	Key Findings	Limitations	Further Research
[78]	Improve MPPT in PV systems	Supervised Learning	MATLAB Simulated PI controller data	SHAP-CatBoost is used to minimize steady-state error during low irradiance and partial shading.	Household	Adjustable MLGB controller outperforms traditional PI with response	Lack of real-world experimental validation	Experimental HIL validation; scalability analysis for microgrid integration
[92]	Accurate RES prediction to reduce consumer energy cost	Deep Learning	NREL, NSRDB dataset	MH-CNN based forecasting model for efficient energy management	Community	Decrease energy bills by 58.32% without ESS and 63.02% with ESS	Limited to residential area	Implementation in a real-world scenario
[93]	Improve short-term wind and solar power prediction	Deep Learning	Chinese State Grid data	CNN-LSTM enhanced with the Coati Optimization Algorithm for hyperparameter tuning	Community	RMSE decreased by 0.5% and 5.8% for 1hr and day-ahead predictions	Potential limitations in the applicability across different environments	Scaling to various geographic and climatic conditions
[94]	Predictive maintenance in wind turbine gearboxes	Ensemble Learning	Vibration and acoustic sensor data	Sensor data were processed using DWT, and by using entropy features faults were classified	Microgrid	92% fault classification accuracy	Stationary load and speed operating conditions	Consideration of dataset imbalance and different condition monitoring schemes
[95]	Estimate global solar radiation and quantify simulation uncertainty	Supervised Learning, Deep Learning	AERONET, BSRN, LIESMARS database	Radiative transfer model coupled with XGBoost, RF, MARS, MLP, DNNs, LightGBM	Small-scale solar PV systems	RTM-RF is most efficient with MAE of 15.57 W/m^2 and R^2 of 0.98	Limited data, less accuracy in cloudy and rainy conditions	Improving accuracy in diverse environmental conditions
[96]	Optimize hybrid solar PV and wind energy generation	Deep Learning	MATLAB environment operating cases	ZOA-ANFIS for MPPT in PV and wind systems; integration of novel HEPMSG design	Microgrid	ZOA-ANFIS computes 26.17% faster for PV and 35.5% for Wind than GTO	Study conducted on a small scale; cost not considered	Including cost optimization in analysis while maintaining performance
[97]	Improve PV panel segmentation for capacity estimation	Deep Learning	Remote sensing images from Germany	GenPV model employing multi-scale feature learning with inductive learning and Focal loss function	Community	Outperformed U-Net and FPN with 0.916 precision and 0.651 IoU.	Difficulty in segmenting small PV panels and similar object	Integration of LiDAR, hyperspectral imagery, and application of explainable AI
[98]	Optimize RES generation by considering cost and life cycle	Supervised Learning	Home Pro simulation, 100 buildings data	Decision tree to forecast life cycle, weighted sum model for optimal decision-making	Community	84% and 54.59% reduction in cost and environmental impact	Algorithm scalability, linear decision-making model	Expansion to different geographic locations and larger scales
[99]	Predictive maintenance of generation equipment	Supervised Learning	Simulated turbine data	Developing a binary classification system for maintenance prediction using DT and ANN	Microgrid	98% accuracy in maintenance identification	Specific to hydroelectric, dependent on the quality of sensor data	Application in other industrial contexts, testing new approaches like SGTM
[100]	Fault detection for PV system operational planning	Supervised Learning	GPVS-Faults data	Three ML models (LR, RF, NB) were benchmarked using classification metrics on a noisy dataset.	Microgrid	0.96 F-score by RF and 1.76 seconds training time	Noisy measurements, scalability issues with LR	Exploration of more efficient algorithms

TABLE 4. Summary of AI studies for energy storage in small scale power systems.

Ref.	Objective	AI Technology	Data Source	Methodology	Scale	Key Findings	Limitations	Further Research
[108]	SOC estimation for lithium-ion batteries	Deep Learning	Localized testing platform dataset	Combined CNN for spatial feature extraction and LSTM for time series analysis	PV energy storage system	0.31% RMSE, 0.18% MAE, with minimal deviation during voltage jumps	Focuses on a specific type of battery and system configuration	Exploration of model applicability to different battery types and larger systems
[109]	Improve SoC estimation for different batteries	Transfer Learning	Lab batteries under different loading conditions	Deep Domain Adaptation Network with domain adversarial mechanism and maximum mean discrepancy	Battery energy storage system	Average error of 1.8% - 2.4% for the target battery	Limited to similar battery chemistries; not considering battery aging.	Exploring model mechanism for transfer learning in SoC estimation
[110]	Monitor and predict Flywheel energy storage remaining useful life	Supervised Learning	Accelerated life test platform PRONOSTIA	PCA for health indicator construction, EMD-Kriging for RUL prediction	hybrid energy storage system	Accurate prediction with RMSE of 0.0425	Verified only under constant operating conditions	Adaptive RUL prediction for variable conditions
[111]	Optimize BESS scheduling with the PV system	Reinforcement Learning	Chungbuk PV distribution data	RL-based optimal scheduling model using various algorithms: A2C, PPO, TD3, SAC	Building PV energy storage system	The PPO model was most effective in maximizing self-sufficiency and economic profits	Data limitations, focus on a specific residential setting	Scale-up to include various battery sizes and regional energy-sharing communities
[112]	Optimal energy storage planning under renewable energy uncertainty	Deep Reinforcement Learning	California ISO curtailment data, Edison TOU plans	A policy-based DRL approach for real-time decisions while considering the stochastic nature of RES.	Microgrid	Outperformed scenario-based stochastic optimization; achieved 90% profit accuracy	Need for extensive training data, potential for overfitting	Enhancing model accuracy and application in larger grid systems
[113]	Predict the remaining useful life (RUL) of lithium-ion batteries	Deep Learning	NASA and CALCE battery datasets	Use of ISSA-LSTM for accurate RUL prediction based on battery capacity analysis	Portable energy storage system	ISSA-LSTM outperformed with 0.0112 MAE and 0.0147 RMSE for CS33	Specific to datasets used	Potential for real-time RUL prediction in electric vehicle batteries
[114]	Predict RUL of lithium-ion batteries	Deep Learning	Severson 124 batteries dataset	Evaluation of 7 ANN models with Feature extraction and hyperparameter optimization	Battery energy storage system	ResNet attains 10.7% MAPE using 30% of data as the training	Complexity in capturing patterns from extensive time dependencies	Exploration of additional architectural configurations and cycle windows
[115]	SOC estimation for Li-ion batteries	Deep Learning	INR 18650-20R and Panasonic NCR18650PF batteries datasets	Multi-variable data was sent to CNN-TCN and RNN layers for temporal and spatial feature extraction to estimate SOC	Battery management system	Over 45% improvement in estimation accuracy with KF integration	Computational Complexity, Limited to specific battery models and dynamic conditions	Optimization of deep learning models and KF for broader battery types
[116]	Optimize energy storage in hybrid grids	Supervised Learning	Solar, wind, and battery simulation data	GA is used for discharge-charge cycle calculation and battery health, and TD-Lambda is used for grid dynamic optimization.	Standalone hybrid grid	Enhanced optimization of load demand, efficient battery health management, and energy pricing	Scalability limitations, Generalization of the Model	Potential for real-time adaptation, refining optimization techniques

TABLE 4. ***(Continued.)*** **Summary of AI studies for energy storage in small scale power systems.**

[117]	Optimize energy storage system operation and maintenance	Reinforcement Learning	Microgrid simulated data	DRL-based framework with imitation learning pre-training to reproduce a user-defined heuristic	Microgrid	15% increase in profit, reduced ESS replacements	Real-world data application, Large computational effort	More accurate ESS degradation modeling, extension to islanded microgrids,

TABLE 5. **Overview of assessment criterion for AI applications.**

AI Acceleration Performance Indicators	
Quantitative KPIs	Qualitative KPIs
a. Cost Effectiveness: Evaluate the cost benefits of AI-based solutions.	a. Innovation Level: Evaluate the novelty or significant improvement of the AI methodology.
b. Demand Management: Assess the effectiveness of AI in reducing energy demand.	b. Practical Applicability: Assess real-world implementation or effective simulation.
c. Prediction Accuracy: Measure the improvement in algorithm forecasting accuracy.	c. Scalability Potential: Examine the adaptability of AI findings to various operational scales
d. Computational Simplicity: Evaluate the computational requirements of AI solutions.	d. Operational Efficiency: Evaluate the effectiveness of AI in managing grid operations.
e. User Comfort: Assess whether AI outcomes maintain user comfort levels or not	e. Reliability in Residential Settings: Assess AI effectiveness in home environments.

applying AAPIs in the development and assessment of new AI-based energy platforms. This standardized approach enables comparing varied AI algorithms, from traditional algorithm-based systems to more advanced, innovative applications such as deep neural network models. To provide context and demonstrate the potential application of the AAPIs, the paper applies the framework to various AI-driven studies in the realm of small-scale electric power systems. As a demonstration, these KPIs are applied to various studies to evaluate their accelerated performance for different applications of electric power systems, as shown in Table 6.

The quantitative assessment of the reviewed literature highlights distinct trajectories in the application of AI across various domains of small-scale electric power systems. Regarding energy generation and energy storage, AI plays a significant role in grid management and operations, energy consumption, and demand response with respect to optimizing renewable energy production in smart grids and managing energy flexibility for demand response and other processes. The advancement in AI technologies, especially deep learning, makes the prediction accuracy more accurate but at the cost of higher computational demand and complex ML algorithms. The assessment of demand management indicates enhanced AI capability in managing energy demand by improving load forecasting and performing complex operational decisions by executing real-time analytics to modulate energy supply in correspondence with consumption patterns. However, energy generation and energy storage register a less pronounced engagement with AI for demand management, implying that current research has not fully exploited the potential of AI in this regard. Fig. 2 demonstrates the comparative performance of key indicators by scoring AI-based reviewed articles in various application areas – such as energy storage, grid management and operations, energy generation, and energy consumption and demand response against the quantitative KPIs of cost-effectiveness, demand management, prediction accuracy, computational simplicity, and user comfort to highlight emerging research trends.

The qualitative assessment of the reviewed articles provides information about the advancement and maturity of AI-accelerated solutions within diverse domains of small-scale electric power systems. In the case of energy storage, AI applications are mainly in the evolving phase as methods are being developed for more accurate battery RUL and SOC predictions. In the same way, AI applications seem more established for grid management and operations due to the proven effectiveness of reinforcement learning in optimizing the decision-making process of integrating and maximizing the use of renewables in microgrids and virtual power plants. Similarly, the higher innovation level in the case of energy consumption and demand response indicates real-world implementation of most of the AI applications in forecasting demand, optimizing energy consumption, and scheduling controllable appliances with more research focused on improving the already developed solutions for better grid operational efficiency. The scalability potential for energy generation shows the dynamic phase of AI solutions, such as federated and transfer learning, in improving renewable energy generation and predicting the maintenance of generation equipment while delving into expanding the impact of AI in larger systems. Fig. 3 highlights the qualitative spectrum of small-scale electric power systems across multiple operational domains ranging from established practices to emerging innovations within energy storage, grid management and operations, energy consumption, and energy generation.

Similarly, the research trends are more oriented towards microgrids with household-level energy management to address various objectives related to renewable energy

TABLE 6. Demonstration of the use of KPIs in evaluating the performance of AI-driven research in electric power systems.

Application Area	Article	Quantitative KPIs					Qualitative KPIs				
		a	b	c	d	e	a	b	c	d	e
Energy Generation	[92]	★	★	★			Evolving	Emerging	Emerging	Evolving	Evolving
	[118]			★		★	Established	Established	Established	Emerging	Established
Energy Consumption and Demand Response	[58]			★	★	★	Established	Evolving	Established	Emerging	Established
	[119]		★	★		★	Evolving	Emerging	Evolving	Emerging	Evolving
Grid Management and Operations	[70]		★				Evolving	Evolving	Established	Established	Evolving
	[120]	★	★		★	★	Evolving	Established	Evolving	Established	Established
Energy Storage	[112]	★	★		★	★	Established	Emerging	Emerging	Established	Evolving
	[121]			★	★		Emerging	Evolving	Emerging	Emerging	Evolving

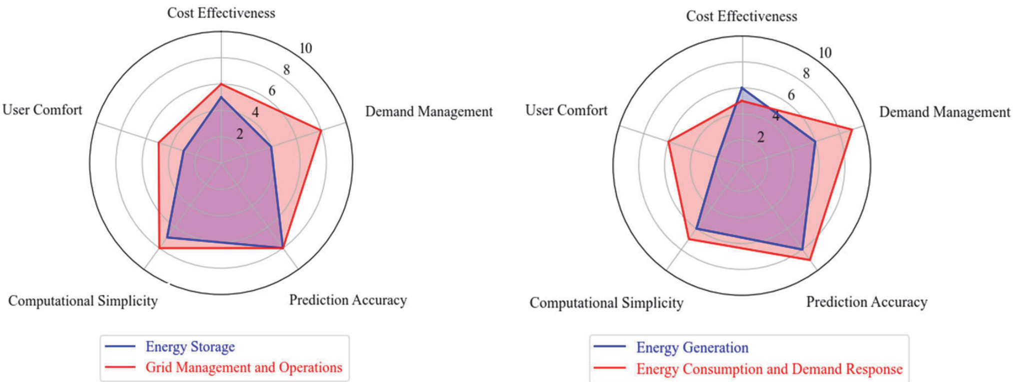

FIGURE 2. Comparative radar charts illustrating the performance of reviewed articles across key quantitative indicators for small-scale electric power systems.

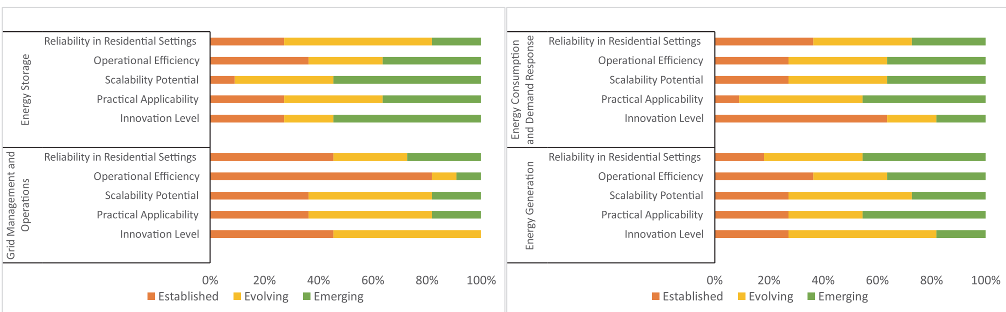

FIGURE 3. Qualitative analysis of AI application across different domains in small-scale electric power systems.

optimization, energy efficiency, and load forecasting. Microgrids-related studies represent 29.4% of the literature, while smart grids and VPPs account for 14.7% and 8.8%, respectively, thus pointing towards a trend of decentralized, consumer-focused energy solutions. Compared to building-level studies, which comprise 13.3% of the studies, household-level studies make up 26.5% of the research, indicating the significant emphasis on AI in the residential sector.

AI applications show promising results in several small-scale power system domains. However, based on AAPI analysis, certain application limitations and areas require further research to fully exploit AI's potential in this sector. Many AI applications are data-dependent and are confined to specific scenarios. For instance, studies using federated learning or interactive learning require large, diversified datasets for training and validation that impact the performance and generalizability of AI models to different environments, operational conditions, and grid configurations. Most of the studies focus on the specific area of energy management systems, such as only consideration of shiftable appliances while lacking integration of thermal models with HVAC control systems, which hinders practical applicability. Computational complexity, data synchronization, and resource demands of advanced AI systems pose significant challenges to scalability and real-time application. AI applications in power systems also pose security and privacy concerns, such as vulnerability to eavesdropping attacks and IoT integration in microgrids that affect reliability in the residential sector. In the case of energy storage, AI-based battery energy storage system shows limited focus on different battery chemistries and aging factors. By incorporating a broader range of datasets, enhancing the processing capability of AI models in dynamic environments, implementing robust security protocols, and exploring unified AI models that can adapt to various power system scenarios related to energy storage and grid management will significantly contribute to the user-centric and feasible AI solution in small-scale electric power systems.

V. CONCLUSION

Small-scale electric power systems have been instrumental in enhancing energy resilience and sustainability. These systems allow for a more flexible and efficient energy management approach, facilitating the local generation, storage, and distribution of energy, thereby mitigating the challenges associated with the integration of renewables. This review paper presents an extensive analysis of AI applications within these systems, highlighting the transformative role AI plays across various aspects of energy generation, storage, and consumption, offering a unique perspective on the future trajectory of AI in enhancing the efficiency and reliability of small-scale electric power systems.

Firstly, a brief overview of small-scale electric power systems' evolution is presented. Subsequently, the review explores their key role in enhancing the resilience and efficiency of modern energy distribution. A detailed analysis of AI across various domains of power systems is presented, from optimizing energy consumption and demand response through smart load management and dynamic pricing to enhancing grid operations with real-time anomaly detection and predictive maintenance. The discussion converges on the AAPIs framework, representing an initial step towards establishing a standardized evaluative framework for AI applications in small-scale electric power systems. This framework incorporates both quantitative and qualitative KPIs, such as cost-effectiveness, prediction accuracy, and innovation level, providing a comprehensive metric for assessing AI technologies. The AAPIs framework reveals significant research trends, with 70% of studies focusing on computational simplicity and only 10% considering user comfort in energy storage methodologies. Conversely, research related to grid management and operations has shown a robust interest in prediction accuracy and demand management, with 80% of articles emphasizing these aspects. Qualitatively, innovation in energy generation has emerged as a critical area with approximately 60% of research marked as 'Emerging', indicating a promising frontier for future research. The AAPIs framework serves not only as a benchmarking tool for current research performance but also guides future AI applications toward achieving user-centric and economically viable solutions.

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Publication VI

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REVIEW

Impacts of grid-scale battery systems on power system operation, case of Baltic region

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Abstract

Grid stability can be affected by the large-scale utilisation of renewable energy sources because there are fluctuations in generation and load. These issues can be effectively addressed by grid-scale battery energy storage systems (BESS), which can respond quickly and provide high energy density. Different roles of grid-scale BESS in power systems are addressed, following optimal operation approaches classification. Furthermore, integrating BESSs into distribution grids is discussed to manage challenges from distributed generation. BESSs aid in voltage control, enhance frequency regulation, and offer black-start services. Aggregating distributed BESSs can provide ancillary services and improve grid economics. For consumers, BESSs optimise energy costs, enhance reliability, and support self-consumption from renewables. Novel BESS services include congestion relief, system adequacy, and power quality enhancement. Moreover, the ancillary services provided in different European countries through BESS are analysed. Finally, a case study was conducted among three Baltic DSOs to analyse the required amendments to Grid Codes and Electricity Market Acts for the integration of grid scale BESS.

KEYWORDS

energy storage, power distribution control

1 | ROLES OF GRID-SCALE BESS IN POWER SYSTEMS

Grid-scale BESS can be utilised for many different purposes in electricity systems. At its core, BESS provides means to store electrical energy for later usage; large grid-scale storage can have a substantial impact on grid performance. This energy could be used to improve the grid reliability and power quality by providing ancillary services such as frequency regulation. Additionally, BESS can provide virtual inertia, which will become especially relevant in future largely RES-dominated grids. The stored energy can be used even out the daily power curve by reducing the peak power. Furthermore, it can enable renewable integration in current grids and postpone grid reinforcement that will inevitably be needed. In this section these roles have been studied further.

1.1 | Grid reliability and power quality impact

1.1.1 | Ancillary service provision

Ancillary services are supportive services that enable the transmission of electrical power from generation to consumption by ensuring that the grid parameters are kept in safe viable ranges. The term ancillary service can refer to a variety of different services but from the perspective of grid-scale BESS what are interesting and what are currently widely being researched are the frequency regulation, voltage regulation, and black start services.

The ancillary service market designs and product descriptions vary from country to country as illustrated by the ancillary services procurement and electricity balancing market design survey [1] conducted by the European Network of Transmission System Operators for Electricity (ENSTO-E). These discrepancies could stem from the historic development of ancillary service markets or the generation mix of these nations. However, the EU has moved towards harmonising the ancillary service markets with the energy balancing guideline regulation [2], which entails that at one point all of the EU member states should start to provide three balancing reserve products: namely the automatic Frequency Restoration Reserve (aFRR), manual Frequency Restoration Reserve (mFRR), that is, secondary and tertiary reserves respectively, and Replacement Reserve (RR). The provision of the primary reserve, that is, the Frequency Containment Reserve (FCR), has not been made mandatory; despite that many nations across Europe are voluntarily implementing it. An illustration of different frequency reserve products is given in Figure 1.

The purpose of the primary control reserve, that is, FCR service is to be the first response to the sudden occurrence of imbalance. Assets that provide FCR activate automatically within 30 s in the entire synchronous are. The activation signal for FCR does not come from the TSO, rather it is based on the continuous measurements of the grid frequency. Adjustments to the production and consumption of FCR providing assets are done proportionally to the grid frequency deviation from the norm. If the frequency deviation persists then the aFRR is subsequently activated [3].

The secondary reserve, that is, the aFRR service will begin to replace the FCR gradually 30 s after the imbalance occurs and reaches the full activation within 5 min. If the grid imbalance persists after 12.5 min of occurring then the mFRR service, that is, the tertiary reserve, starts gradually activating reaching the full activation at the 15-min mark and has a minimum delivery period of 5 min [3].

The last source of reserves, that is, the replacement reserve (RR) uses generators with longer start-up time to either complement the previous reserves or to release them back into their state of readiness. The RR has to reach full activation within 30 min of the disturbance and has a minimum delivery period of 15 min [3]. An alternative could be to instead use large grid-scale BESS. Battery storage can be a good alternative

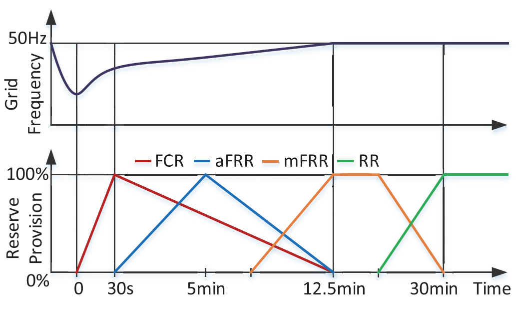

FIGURE 1 Illustration of frequency reserve product activations based on ENTSO-E grid codes.

due to its fast reaction speed, and environmental friendliness when used in combination with RES.

From the experience of the operation of Zurich 1 MW BESS that is used for FCR, peak shaving, and islanded operation; the main challenge for the provision of FCR is the management of the state of the charge (SOC) shifting, which is complicated by the internal losses of the battery and the activation signals that are generally not zero-mean [4]. The relation between the required energy capacity with respect to power capacity was found to be around 220 kWh per MW for FCR provision [5]. The effectiveness of BESS to provide ancillary services is investigated within the PRESTO (Primary REgulation of STOrage) research project [6], in particular by managing the storage SOC with variable droop control.

The profitability of grid-scale battery systems for purposes of Primary Containment Reserve (PCR), peak-shaving (PS), and Enhanced Frequency Response (EFR) was analysed in Ref. [7]. It was found that EFR purpose has the highest profitability of the three; however, combining EFR and PS applications improves the profitability even further.

Grid-scale BESS usage for FCR in a low inertia grid using grid-forming and grid-following methods was investigated in Ref. [8]. It was found that large-scale BESS can significantly improve system frequency containment, especially in the grid-forming converter control mode. Future smart grids will also inevitably encompass smaller distributed battery systems. The authors of Ref. [9] combined smaller BESS, RES, and flexible loads to create one large virtual energy storage system (VESS) for the purpose of voltage regulation. An overview of ancillary service provision with different types of ESS including BESS is given in Ref. [10], where it was found that the overall deployment cost of microgrids is reduced with the utilisation of ESS for ancillary services.

1.1.2 | Virtual inertia emulation

With the increasing RES penetration, the conventional synchronous generation is starting to be phased out. The future grids will undoubtedly have more converter interfaced generation which will result in the reduction of grid inertia. The grid needs to have an adequate level of inertia to maintain a stable grid voltage and frequency. With a low level of inertia, the imbalance between the generation and consumption will start to negatively affect the grid parameters much sooner than in the case with higher levels of inertia. Ensuring an acceptable balance will be even more difficult on a smaller microgrid scale. One novel technique to increase the grid inertia would be to perform virtual inertia emulation with large grid-scale BESS.

Virtual inertia emulation works by imitating the inertial response of traditional synchronous generators (SG). The implementation of virtual inertia is based on the swing equation of SG that is incorporated into the inverter control so that the typical inertia less inverter could emulate the inertial characteristics of SG. It is considered “virtual” since the inertia is emulated without the utilisation of any rotating mass [11].

In general, the implementation models of virtual inertia emulation can be divided into three main categories [12].

- *Synchronous generator model* is based on operating inverters as synchronverters, that is, as inverters with similar dynamics to SG [13]. This is achieved by detailed modelling of electrical and mechanical parts of SG. Integration of this model into solar and wind production is explored in Ref. [14] and for a battery system in Ref. [15].
- *Swing equation*-based is based on operating inverters with only the swing equation of SG rather than modelling the entire electrical and mechanical parts. This method works by measuring the grid frequency and the active power output of the inverter. One well-known method for this is the Ise Lab's topology [16].
- *Frequency-power response* is based on the idea of emulating the ability of SG to respond to frequency changes. This approach is considered as one of the simplest methods of providing virtual inertia since it does not involve a detailed SG model. One well-known method in this category is the virtual synchronous generator (VSG) [17]. The main shortcoming of this method is that if the converter has to operate as a grid forming unit in islanded mode then it can't provide virtual inertia at the same time.

The impact of different levels of minimum inertia constraints with two decarbonisation scenarios was investigated in Ref. [18]. The authors concluded that setting minimum inertia levels may be useful during the transition phase to higher RES penetration levels, however, if not replaced in a timely manner they might end up impeding emission goals. Virtual inertia was used to suppress voltage fluctuations using a BESS in a DC microgrid with a large share of renewables in Ref. [19]. Optimal BESS sizing for virtual inertia emulation in islanded microgrid operation scenario was performed in Ref. [20]. The authors of Ref. [21] concluded that the problems of inertia and frequency stability of power systems with large-scale renewable generation could be addressed with wind turbine emulated inertia, integration of energy storage systems, and involving smart controllable appliances of prosumers.

1.1.3 | Peak power reduction

Peak power reduction, that is, peak-shaving entails a power reduction from the grid during morning and evening peak periods of consumption. During this period the power is supplied by a large energy storage system such as a BESS. The energy stored in the BESS is consumed during off-peak periods when the consumption is lower; at night time or during the daytime when the PV production is highest. With increasing renewable production, it will be crucial to have an adequate level of storage to shift the overproduced energy to mornings and evenings.

Compared to frequency regulation, which is a short-term power-intensive application, peak shaving is a more long-term energy-intensive application. Usually, the peak shaving process needs to be performed for the duration of 1–10 h [22], highlighting the need for large grid-scale energy storage. The main objective of reducing peak power is to alleviate the issues surrounding grid over-loading, reduce the ramp rate during peak consumption, and postpone the need for grid infrastructure reinforcement [23].

An overview of existing peak shaving implementation strategies and challenges based on energy storage systems (ESS), electric vehicles (EV), and demand-side management (DSM) has been given in Ref. [24]. It was found that challenges surrounding EVs are their availability, aggregated control, and lack of large-scale deployment. The challenges with EVs are regarding the customer willingness, presence of proper ICT infrastructure and the overall complexity of the system. Nevertheless, implementing peak shaving using BESS faces challenges of scheduling the optimum operation, optimal sizing, and high capital and maintenance costs.

A decision-tree-based peak shaving algorithm has been developed in Ref. [25] to mitigate peak demand complications in an islanded microgrid with a grid-scale BESS resulting in cost-savings from economic arbitrage, postponed system upgrades, reduced fuel consumption, losses, and carbon emissions. The authors expanded this research for a PV-BESS hybrid system in Ref. [26].

Currently, peak shaving using battery storage might be too expensive of an option, especially in places that are suitable for other large-scale storage systems such as pumped hydro or compressed air storage. However, BESS could be considered as an option in locations that lack the specific geographical features needed for those storage types [27, 28].

1.2 | Renewable energy integration

The ever-increasing renewable penetration has introduced challenges from the power system side that mainly stem from the intermittency and the variability of RES. These challenges have led to a growing need for grid-scale storage. The following BESS applications can further facilitate the integration of renewable energy [29]:

RES energy shifting addresses the intermittency of RES. This is because the most prominent renewable sources such as wind and PV are intermediate by nature and thus might produce at times when not needed or vice-versa. RES energy shifting entails incorporating BESS into the existing power system to store the surplus renewable energy. This can be especially relevant in PV-dominated grids that have high production peak during the daytime which might result in an overproduction that would otherwise be curtailed as illustrated in Figure 2.

RES variability smoothing tackles the variability of RES. Traditionally, renewable energy sources are considered non-dispatchable, meaning that their power output cannot be controlled by the operators dynamically. Although modern control rooms dispatch wind, this is more just limiting their output rather than balancing dispatch. Solar and wind power plants produce energy when the sun shines or when the wind

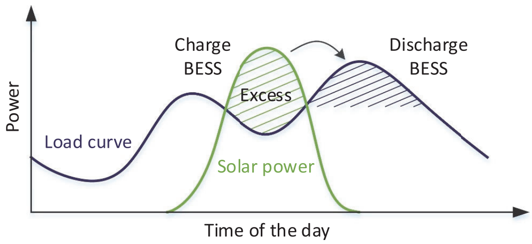

FIGURE 2 Daily excess RES energy shifting.

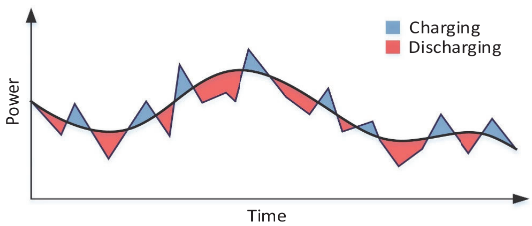

FIGURE 3 Short-term RES variabilitsy smoothing.

blows, but neither of those is guaranteed to be constant. Due to the stochastic nature of renewable sources, there is a need for short-term power smoothing that reduces the sharp ramping changes as shown in Figure 3. The sharp ramping rates are especially troublesome in the case when RES has a large contribution to the generation mix. Power smoothing requires far less energy storage than load shifting [29]; however, since it is a continuous process that is accompanied by frequent charging and discharging it results in faster degradation of BESS. A literature review of control strategies for wind power output smoothing with BESS has been given in Ref. [30]. A bibliometric review of articles related to renewable energy integration with BESS has been given in Ref. [31].

1.3 | Environmental impact

The applications of grid-scale BESS can have a positive effect on the environment. As discussed beforehand, grid-scale BESS can facilitate the integration of more renewable energy into the generation mix which would increase consumption of more environmentally friendly sustainable energy, while at the same time, the traditional generation would be phased out. The authors of Ref. [32] investigated the potential of grid-scale battery systems to replace combined cycle gas turbine (CCGT) plants in responding to variable peak demand in the UK. It was found in the future projection of 2035 that in the UK around 5.5 TWh of battery storage would be needed to replace the energy that would otherwise come from CCGT plants.

Utilising grid-scale BESS for the purpose of grid reliability and power quality can also have a positive impact on the environment by replacing the traditional fast-reacting peaking plants that are usually based on fossil fuels. An example of this would be the work of the authors of Ref. [33], who replaced diesel generators in a university campus microgrid with an unreliable grid power supply with a PV-BESS hybrid system that reduced peak-hour energy purchases from the grid significantly by phasing out diesel generators almost entirely. The authors also concluded that the transition to a PV-BESS hybrid system yielded substantial annual savings and calculated the payback period to be around 6 years.

Nevertheless, when dealing with large grid-scale battery systems the environmental impact of their production, transportation, and recycling needs to be accounted for. Other grid-scale storage types such as pumped hydro and compressed gas storage have comparably trivial environmental and health impacts [34] since they don't require the mining, refining, and recycling of potentially hazardous elements. A review of life cycle assessment (LCA) studies was conducted in Ref. [35] which found that producing 1 Wh of storage capacity is across all battery chemistries on average associated with a cumulative energy demand of 328 Wh and greenhouse gas emissions of 110 gCO_2eq. The potential end-of-life options for batteries could include reuse or repurposing for a "second life", recycling to recover materials, and disposal [36]. Presently less than 3% of lithium-ion batteries are recycled [37], however in the near future the increased demand coupled with restricted access to virgin materials is hoped to increase the recycling rate.

2 | OPTIMAL GRID-SCALE BESS OPERATION APPROACHES

The charging and discharging behaviour of BESS can be implemented with different approaches. Independent of the BESS size, small, medium or grid-sized, three basic operation approach categories need to be considered to determine the optimal method. The first category is conventional operation approaches that is based on traditional control methods, like droop control [36]. The second category is based on heuristic operation methods [37, 38]. These methods do not claim to be perfect, optimal or even rational. Instead, they try to present a practical and satisfactory solution for complex systems, like techno-economic optimisations [39]. The third category is meta heuristic approaches. Which is based on general applicable optimisation algorithms that might be tailored to the problem that needs to be solved, like particle swarm optimisation [40]. These three categories are discussed in more detail in the following subchapters.

2.1 | Conventional

Conventional operation approaches for grid-scale BESS are presented in several publications. These methods are often focused on basic control strategies to provide ancillary services. The comparison of different presented operation approaches is shown in Table 1.

The comparison shows that all the provided publications aim to provide ancillary services, especially primary reserve,

TABLE 1 Comparison of conventional operation approaches.

Publication	Method	Power/Capacity	Position LV, MV, HV	Cell technology	RES integration	DR integration	Geo location	Services
[36]	Droop control	–	MV	–	+	–	Milan, Italy	Ancillary (primary reserve)
[41]	Droop control	5 MW, 5 MWh	–	Li-ion	–	–	Germany	Ancillary (primary reserve)
[42]	Droop control	16 MWh	–	–	–	–	Baja California Sur, Mexico	Ancillary (primary reserve)
[43]	Droop control	200 MW, 100 MWh	–	–	–	–	United Kingdom	Ancillary (primary & secondary reserve)
[44]	Droop control	10 MW	–	Li-ion	–	–	Northern Ireland	Ancillary (primary reserve)
[45]	Model predictive control	20 MW, 80 MWh	–	–	+	+	–	Ancillary (primary reserve); operation cost reduction (real time price)
[46]	Droop control	225 MW, 175 MWh	HV	Lithium-Titanate-Oxide	–	–	Europe	Ancillary (primary reserve, restoration)

Note: + = considered/integrated; − = not mentioned/integrated.

with the conventional operation approaches for grid-scale BESS. Since this is directly related to frequency control, nearly all proposed methods are based on droop control approaches. As expected for grid-scale BESS, the power and capacity considered are in the MW/MWh range. Unfortunately, it is often not mentioned, on which voltage level the BESS is connected, but the two mentioned levels are medium- and high voltage levels. The popular battery cell technology is lithium-ion based. Eight of the 9 publications use simulations, whereas only 1 publication presents an experimental setup for research. Due to the droop control implemented in most of the publications, renewable energy sources and demand response are not directly integrated into most of the conventional battery operation approaches.

Apart from this scientific literature which is based mostly on simulations as the comparison shows, there are multiple TSOs and DSOs that started implementing large battery storage into their grids. Of course, based on the TSOs and DSOs main interests, these systems are controlled by conventional algorithms, like droop control, to provide ancillary services to the grid and improve the power quality this way. Examples for those implementations worldwide would be in USA [47], United Kingdom [48], Australia [49], Denmark [50], or Germany [51, 52].

2.2 | Heuristic

The most popular operation approaches for grid-scale BESS are heuristic methods. There is a wide range of publications that present different heuristic approaches to build a coordination framework not only for battery storage but often in combination with larger renewable generation sites. A comparison of different presented heuristic operation methods is shown in Table 2.

In heuristic operation approaches for grid-scale BESS, there are often multiple objectives that are considered. These include not just ancillary services but also economic, environmental and local power quality focused goals. For these goals, there are different approaches presented in every publication. These reach from energy market based control decisions to combinations with conventional approaches and prediction based models. Unfortunately, for some of these articles the grid scale BESS start at medium capacities, like 20 kWh, but most of them consider the MWh-range as expected. Like with the conventional methods, the preferred battery cell type is lithium-ion based. Due to the multi-objective orientation of these operation strategies, there is a direct integration of renewable energy sources and/or demand response into most of these control methods. Like the conventional methods, these operation strategies are simulation based as well.

2.3 | Meta heuristic

There are many publications that present different meta heuristic operation approaches for BESS, such as particle swarm optimisation [40] or discrete-time-gradient optimisations [59]. However, most of these publications present operation approaches in the framework of small or medium microgrids. In the context of grid-scale BESS the number of available

TABLE 2 Comparison of heuristic operation approaches.

Publication	Method	Power/Capacity	Position LV, MV, HV	Cell technology	RES integration	DR integration	Geo-location	Services
[53]	Setpoint adjustment, over fulfilment, use of deadband, use of gradient	5 MW, 5 MWh	MV	Lead acid, Li-ion (LMO, LFP)	–	–	Germany	Ancillary (primary reserve)
[54]	Real time- (TSO/DSO frequency signal based), predictive (feed-in-tariff based) control	20 kWh	LV	Li-ion	+	+	–	Ancillary (primary& secondary reserve); increased self-consumption; operation cost reduction (demand response)
[39]	TSO/DSO frequency signal based, intraday energy market (15 min based), peak shaving (monthly & daily model)	1 MW–5 MW, 1 MWh–30 MWh	–	Li-ion	–	–	Germany	Ancillary (primary reserve& secondary reserve); peak shaving; black start
[55]	Decision-based control algorithm with optimisation	5 MW, 5 MWh; upscaling to > 50 GWh	–	Lithium-manganese	+	–	United Kingdom	Ancillary (secondary & tertiary reserve)
[56]	Techno-economic model based algorithm	>1 GWh	–	Li-ion	+	–	United Kingdom	Ancillary (secondary & tertiary reserve)
[57]	Multi-objective optimisation, energy market based (day-ahead),	<200 kW, <200 kWh	MV, LV	Li-ion	+	–	–	Economic optimization; peak shaving; increased self-consumption;
[58]	Corrective voltage control	>300 MW	-	–	+	–	–	Local reactive power control; local voltage control; local power/voltage control

Note: + = considered/integrated; – = not mentioned/integrated.

publications is reduced to a few relevant ones. A comparison of the presented approaches is shown in Table 3.

As mentioned before, the number of meta heuristic operation approaches for grid-scale BESS is more limited than the other approaches. The presented methods implement a general optimisation technique in the control strategy, namely particle swarm-, discrete-time-gradient- and generic optimisation algorithms. However, the capacity considerations for those methods seem to be set between medium and grid-scale level. This is also shown in the presented voltage level connection. Many publications show smaller sized BESS of less than 100 kW with meta-heuristic operation approaches. This indicates a higher popularity of these methods on microgrid-scale to primarily achieve an optimised operation for a private investor or customer rather than the DSO or TSO. As with the two previously discussed methods, lithium-ion cell technology is preferred as well as simulations instead of experimental setups. All methods integrate only renewable energy production and do not consider demand response methods. The focus of these publications is, as expected for medium scale BESS, on microgrid services, like increased self-consumption and operation cost reduction. Ancillary services are not considered at all.

In summary, the three different operation approach categories are oriented at specific goals. While conventional approaches are focussing on ancillary service provision, heuristic and meta heuristic approaches are tailored to provide maximum cost reductions with multiple objectives. Based on that, it can be concluded that heuristic and meta heuristic grid-scale BESS control is most suitable for private investors, as their goal is cost saving and quick return-of-investment. For TSOs and DSOs, conventional control methods are the best fit, as their primary goals are grid stabilisation, reliability, and power supply security. This is confirmed by the examples of practical implementations of TSOs and DSOs with grid-scale BESS which are all based on conventional operation methods.

3 | PARTICIPATION OF GRID-SCALE BESS GRID SERVICES TO OVERCOME POWER QUALITY ISSUES

All electrical devices require the voltage level to remain within a certain magnitude and parameters. The required voltage levels and parameters are determined with European Standard EN 50160 [68]. The standard defines, describes, and specifies the voltage regarding its frequency, magnitude, waveform, and symmetry of the line voltages and is addressed as power quality in the professional literature. Voltage related power quality events (power surges, sags, transients, momentary interruptions, etc) are usually caused by external events that is, weather (high winds, lightning), starting and stopping heavy equipment (motors driving mechanical processes, utility switching), circuit overloading or system failures (short circuits, fault clearings, wrong dimensioning of system). If previously most of the power quality issues could be omitted to consumers and power electronics driven non-linear loads [69–72], then in the past years, growing concerns regarding the electricity consumption and production's impact on the environment have introduced a new set of sources for power quality issues – low carbon technology. The European Green Deal [73], The 2030 Climate and Energy Framework [74], and the 2050 long-term strategy [75], have the aim of the EU to become climate-neutral by 2050. To accomplish this, governments are creating different incentives for energy end-users and producers to invest in low carbon technologies, that is, photovoltaics (PV), wind energy (WE), electric vehicles (EV), battery energy storage systems (BESS), and similar. As the load demand keeps growing and the integration of stochastic

TABLE 3 Comparison of meta heuristic operation approaches.

Publication	Method	Power/Capacity	Position LV, MV, HV	Cell technology	RES integration	DR integration	Geo location	Services
[40]	Particle swarm optimised fuzzy control	110 kW	LV	Li-ion	+	–	–	Increased self-consumption
[59]	Multi-timescale and discrete-time-gradient optimisation	>100 MW	–	–	+	–	–	Operation cost reduction (day-ahead & 15 min); balance RES & load
[60]	Genetic algorithm	200 kWh–700 kWh	MV	Li-ion	+	–	–	Operation cost reduction (day-ahead)
[61–67]	Genetic algorithm, artificial bee colony, grey wolf, particle swarm, wild horse;	<100 kW	(LV)	–	+	+/–	–	Increased self-consumption, operation cost reduction

Note: + = considered/integrated; – = not mentioned/integrated.

generation increases, new challenges arise in the power system operations.

3.1 | Power quality issues caused by stochastic loads and generation

Although renewable electricity generation from weather-influenced sources introduces uncertainties on the generation side, the load side can introduce similar uncertainties due to market price-driven demand-side management actions. Coinciding stochastic events on both the generation and consumption can lead to voltage and frequency events as described in Refs. [76, 77]. Another issue that might arise in power systems with high penetration of renewable generation is the increased need for ancillary services to mitigate the possible stochastic generation down curtailment and the corresponding loss of energy, as discussed in Refs. [78, 79].

3.1.1 | Stochastic loads

Authors in Ref. [80] prove with numerical simulations that the stochastic nature of the load can suddenly make the system lose its voltage stability. According to Ref. [81], residential loads are subjected to variations that are biased with the household's inhabitant's lifestyle. The latter can help classify household loads according to its inhabitant's lifestyles and level out specific stochastic characteristics, but eventually, a certain amount of unpredictable variability remains. Furthermore, with the increasing share of renewable electricity generation assets and deregulated operation of the energy markets, novel services (i.e., demand-side management) introduce yet another level of variability to the load that is hard to forecast to a certain magnitude. Economics-based shifting of loads can accumulate unwanted power quality parameters to limited periods where otherwise evenly distributed power quality phenomenon is magnified to an unaccepted level, putting additional strain on the distribution network. Most electricity consumers with integrated renewable energy sources are connected to the low-voltage distribution system. This system already includes a high number of single-phase loads, and together with the distributed generators (DG), they could cause unwanted effects in distribution networks, as discussed in Ref. [82].

The majority of residential electricity consumers are single-phase loads and together with uneven loading of the phases causes an existing voltage to unbalance phenomenon in the distribution grid. Single-phase PV-s, residential battery energy storages, and home electric vehicle charging stations could further increase the voltage unbalance in the network. According to scientific literature [82, 83], voltage unbalance causes issues with induction motors as it raises the temperature, increases losses, and lowers their efficiencies. Additionally, the voltage unbalance is often accompanied by negative sequence voltage that causes negative sequence current, which does not do any useful work and contributes to energy losses and decreased transmission capacity in the distribution lines. From the perspective of the load, the most important factors are the load power variation speed and its magnitude, as described in Ref. [76]. Such variations, for example, could be introduced by plug-in electric vehicles [84, 85], as every different car plugged in for charging could introduce different load profiles depending on the manufacturer, battery capacity, charging technology, the initial state of charge, ambient temperature, etc.

According to numerous tests carried out on 68 different EV models in Refs. [86, 87] the charging capacity amongst different EVs can remain between 27 and 205 kW (average 92 kW), whilst the duration remains between 18 and 51 min (average 32). It should be noted that the charging experiments were carried out in public fast-charging facilities, meaning that such large variability in duration and capacity is stochastic and could occur in the system any time of the day. Although the energy consumption remains relatively stable (47 kWh on average), the load variation speed and magnitude can change significantly. According to the International Energy Agency's report [88], the global electric vehicle market has doubled roughly every 2 years. With the rapid changes imposed by stochastic charging activities, such a trend inevitably increases the difficulty of keeping an acceptable voltage profile in the distribution systems [89]. Fast-changing loads with high magnitudes could cause over- and under voltage events since the dedicated system elements (i.e., transformer on-line tap changers or reactive power support devices) have an unavoidable delay in adjusting to the new system state. The growing number of electric vehicles and home chargers contribute to the voltage drop and the total harmonic distortion (THD) that could exceed the set boundaries by standards in the low voltage distribution networks as discussed in Refs. [82, 90]. Additional THD sources are power-electronic devices that are widely used in home appliances for example, TV sets, personal computers, compact fluorescent lamps, LED lamps, and similar. The concurring harmonics increase losses (similarly to the negative current components) and deteriorate equipment life span due to additional heat dissipation [91]. The large increasing share of power-electronic driven electric vehicle home chargers and time shifting of loads could eventually lead to a situation where the THD of the low voltage distribution network exceeds the safe and recommended operational values. A study [91] showed that when electric vehicle penetration reaches 70% (with three-phase rectifier chargers), the fifth order harmonic level in the distribution network is doubled. Another study [92] indicated that low voltage distribution networks could have issues with transformer capacities and low voltage line thermal ratings when the electric vehicle penetration in the grid reaches 40%.

With the paradigm shift currently occurring in the power industry, it is essential to develop the energy demand and supply domain and manage and develop the control and hardware of the physical system. Without the integrated approach, considerable challenges hinder reaching the climate neutrality target. In future distribution grids, the following five aspects need to be addressed regarding the impact of stochastic loads on power quality:

1. The capacity of transmission/distribution equipment
2. Harmonic distortion
3. Voltage unbalance
4. Overvoltage
5. Undervoltage

3.1.2 | Stochastic generation

Mainly two factors pose challenges for grid integration of renewable systems: the variability and the decentralisation of energy generation. For example, the variability of solar power occurs in two stages: the first stage is variability over day and night, the second stage is due to solar irradiation fluctuations caused by intermittency of clouds. Similar variability can be omitted also to wind power as described in Refs. [76, 92, 93]. The reliability of the electrical grid is endangered by the high penetration of such volatile energy sources, causing problems in balancing supply and demand, voltage instability and power quality [94]. Decentralised energy generation mitigates problems in transmission grids, for example, reduced line losses, but can induce new problems in distribution grids, such as overvoltages, and requires new operation strategies [95]. Another aspect to consider is that traditionally the low voltage distribution grids have been unidirectional regarding power flows – usually towards the loads. As the distribution networks were initially designed to serve loads, the high penetration of local renewable energy production can lead to network congestions as coinciding generation peaks tend to occur irrespective of the residents' lifestyles.

Authors in Ref. [89] discuss that the stochastic nature of weather dependant renewable energy sources pose challenges for the currently used voltage management devices, that is, online load tap changing (OLTC) transformers, voltage regulators (VR), or shunt capacitors and reactors. While the weather impacted generation can have sudden changes in power output in a matter of seconds, then the voltage regulating devices tend to have longer reaction times due to their mechanical switching nature. From one side, this causes excessive wear and tear on the voltage regulating devices resulting in a shorter lifespan but, in worst cases, can lead to generation curtailment or even switch off due to network protection algorithms. In addition to sudden voltage changes, the high penetration of distributed energy resources can also impact the power quality on several levels [83]. Rapid voltage changes might lead to varying light intensity, also perceived by the human eye, known as flicker. Single-phased PV-s can lead to and contribute to unallowed voltage unbalance. According to Ref. [82], a high number of single-phase low carbon technologies (PVs and electric vehicles) can increase the voltage unbalance in single nodes and the entire low voltage network. The stochastic nature of the PV-s output can increase the voltage unbalance fact in the distribution system during specific periods of the day if compared to a system without PV-s installed.

Since small-scale renewable energy sources are coupled to the grid through power electronic devices, they tend to impact the harmonic distortion in distribution systems. With the large-scale integration of low carbon technology to our low voltage distribution grids, it is becoming more challenging to satisfy the required level of power quality [96]. In future distribution grids, the following five aspects need to be addressed regarding the impact of stochastic generation on power quality:

1. The capacity of transmission/distribution equipment
2. Harmonic distortion
3. Flicker
4. Voltage unbalance
5. Overvoltage

3.2 | Battery energy storage systems for power system services

BESS-s are an important enabler for the integration of stochastic and renewable generation installations not only on grid level, but also near prosumers. BESS-s increase flexibility in balancing supply and demand but can also increase safety, reliability, and quality of distribution grids by performing ancillary services for frequency stability, voltage stability and availability of energy and power reserves for balancing. As European Union is parallelly promoting the transition of the traditional generation-centric ancillary services energy market towards a market with an increased role also for prosumers [97], participating in ancillary services provision could make the investment in BESS-s economically more feasible [78] and at the same also enhance the possibility and performance of demand-side response.

BESS-s have the possibility to provide a variety of ancillary services. More generic ancillary services today mainly focus on voltage regulation [98–100] or frequency regulation [101–109]. The following table (Table 4) adopted from Ref. [110] and modified according to ENTSO-E and European Union terminology summarises the traditional ancillary services that could be delivered with battery energy storages to different target groups. The target group includes three main fields of activities: system operators (also including transmission system operators, distribution system operators and any other operational forms, that could be present), utility companies (mainly owners of assets, including generation, storage, lines, etc.), and electricity consumers (residential, industrial, commercial, etc.).

3.2.1 | BESS services for the TSOs and DSOs

Authors of Refs. [98, 99, 107] discussed advanced methods in voltage control strategies to meet the challenges that arise due to the large amount of distributed generation penetration into the distribution grids. The idea of using BESS for voltage

TABLE 4 Battery enabled traditional ancillary services, their definitions, target groups and coverage in scientific literature.

Service name	Definition	Target group	Papers
Load-frequency control and regulation reserves	Mechanism used to restore the balance between load and generation within a control area to maintain the power frequency in the desired range to avoid grid instabilities.	System operators	[79, 101–109]
(Spinning) energy reserves	Generating capacity that is either online (spinning) and instantaneously available or available in the matter of minutes (usually <15 min) and can provide output in response to contingency events (e.g., generation or interconnection trip).	System operators	[78, 101–109]
Voltage support and regulation	Mechanism that ensures the voltage level in the power system is kept within acceptable operations range and to avoid system wide incidents that is, voltage collapse, or inefficient operation conditions.	System operators	[98–100]
Black start capability	In the event of total system failure that causes grid outage, the ability to bring a regional part of the grid back online without external grid connection.	System operators, utility companies, electricity consumers	[111–114]
Energy cost optimisation	Also known as energy arbitrage or storing power purchased at off-peak times and selling it on-peak	Utility companies, electricity consumers	[78, 79, 94, 97, 115–120]
Increased distributed generation self-consumption	Minimising the export of stochastic and distributed renewable generation produced electricity from a region during low consumption periods and utilising it during high consumption periods.	Electricity consumers	[100, 115–120]

regulation lies in the controlled charging and discharging of the BESS according to the operation of distributed generation and the corresponding voltage level fluctuations in the distribution system. Additionally, the authors of Ref. [100] bring out that the integration of BESS into the voltage control strategy in distribution systems could increase the life expectancy of on-load tap changers and step voltage regulators that otherwise would suffer from the increased workload and shorter lifespan due to the additional work cycles caused by the distributed generation.

Authors of Refs. [101, 104, 108] discuss the challenges posing in utilising batteries for frequency regulation. A special control system could also overcome the issues associated with more frequent usage of BESS for frequency regulation that increase the operating costs or decrease the battery lifetime. The authors of Refs. [102, 103] on the other hand discuss and validate the possibility to use distributed BESS-s to provide FCR (or primary reserves, as usually referred to in specialised literature) in Germany. The importance of the pilot project lies in the fact it successfully demonstrated the possibility of a distributed storage capacity successfully providing services that were previously provided by large conventional power plants. Authors of Ref. [105] discuss about the suitable dimensioning of the BESS unit for FCR provision in wind dominated power systems, Brogan *et al* in Ref. [106] analyse the minimum requirements for BESS to participate in frequency control activities and during a high and low rate of change of frequency events. The author of Ref. [109] brings in yet another aspect that BESSs could be suitable for that is, distributed control of BESS to prevent under-frequency load shedding. All the previously mentioned papers bring out the challenges of large-scale renewable energy penetration and the lack of ancillary services from a conventional generation that is being actively phased out due to the changing energy policy and increasing share of renewables.

Additionally, BESS-s combined with weather impacted generation could provide a viable alternative for black start ancillary services that are currently provided with conventional generation units. Authors in Ref. [111] discuss the possibility to combine wind power plants with energy storage systems to provide black-start power. If traditionally the black-start power is provided with thermal, nuclear, or hydropower, then the instability of the output of the wind power plant is one reason that these assets are seldom used as a black-start power resource. The paper proposes a method of energy storage configuration to enable this possibility with wind power plants. Similarly, to wind power plants also PV-s is neglected when discussing black-start capability. Authors in Ref. [112] discuss the challenges to combine BESS-s with PV installations to provide black-start capability. The key challenge is caused by the random output of the PV installation and high variability of power and energy during black-start events that could lead to either over-charging or over-discharging of the BESS. With suitable control and optimisation algorithms, these issues can be overcome and could provide a valuable alternative source of black-start capacity. Authors of Refs. [113, 114] discuss about the possibility to use the BESS to provide black-start capability for the distribution system with either a single unit or with a multi-energy storage power system. Generally, all authors come to the same conclusion that BESS-s are a universal asset that can extend the black-start capability of a variety of technologies. More than that, in order to enhance power system resilience, battery energy storage systems (BESS) play an integral role in addressing power system events and outages. In these scenarios, BESS operation involves rapid response to imbalances in supply and demand, frequency deviations, and voltage fluctuations. To maintain grid stability during sudden load changes or power outages, BESS can quickly inject or absorb power. Backup power from BESS can ensure essential services are maintained during longer outages. Having fast response capabilities and flexibility, BESS can mitigate the impact of power system disturbances, ensure uninterrupted power supply, and contribute to overall grid resilience.

In addition, the versatility of BESS cab be further increased through the aggregation of distributed battery assets. This way even the distributed BESS-s could be used to provide similar services as large-scale bulk energy storage units, as discussed in Ref. [121]. The aggregation of distributed BESS assets in distribution grids are suitable for providing ancillary services meanwhile also increasing their economic performance. With the increasing share of stochastic renewable energy production, the planning and maintaining the main grid becomes ever more challenging and with higher operational cost. BESS, both on distributed and centralised levels, could be one possible solution to help transform the energy sector to a more decentralised and less carbon-intensive without compromising the security of supply or making it too expensive to hinder its further development. BESSs could be the versatile link to speed up this process, due to it possibility to cope with many of the existing issues starting from localised problems (voltage quality, congestion relief, etc.) to a more centralised alternative to traditional generating capacity provided services (frequency, control, voltage control, asset adequacy, etc.).

3.2.2 | BESS services for consumers

BESS are mainly marketed for their energy cost optimisation through retail energy time shift, peak shaving, and increased self-consumption from distributed generation through behind-the-metre solutions as discussed in Refs. [79, 100, 115–120, 122]. Also, the power reliability can be increased through BESS usage in weak grid locations to cope with voltage sag ride though and provide back-up power and even island solutions [123]. Although these services are mainly targeted at residential customers, then as discussed before, with coordinated control these BESS units could be used also for ancillary service providers, and thus increase the added value created by BESS units for both their owners and the society. Otherwise, the market prices are not favourable to make the BESS economically viable for all residential customers as discussed in Refs. [115, 117, 120]. Other aspects that hinder the benefits from increased self-consumption are location-based limitations to distributed renewable generation as discussed in Refs. [116, 119], making it even clearer that BESS systems should combine different services provision (e.g., ancillary services) to make them economically viable. The increasing demand for electricity and substituting traditional generation with stochastic technology also increases the strain on the physical network. Novel solutions are needed to cope with both operational and planning challenges of the power system. Both, the consumer and power and utility companies, can benefit from it though increased socioeconomic welfare.

3.2.3 | Novel services with BESS

Novel ancillary services from BESS-s include congestion relief [124–128], transmission/distribution system adequacy related services [127, 129–131], and power quality-related issues [98, 132–138]. Authors of Ref. [124] describe a case study where the battery located at a congestion point can provide backup energy storage during a contingency event to relieve thermal overload, thereby allowing the transmission limit to be increased. Although not specified, authors of Ref. [125] discuss the distribution system level optimisation of different assets (including energy storage) to avoid congestion during intraday operation. Authors of Ref. [126] propose to include the energy storages as service within a sharing economy concept to relieve transmission congestions by utilising the idle capacity on the open market for a fee, while in Refs. [127, 131] the authors propose a similar solution but instead with the energy storage capability of electric vehicles. Also, the possibility to utilise energy storage to defer upgrade of the existing electric grid infrastructure is introduced in Refs. [127, 129–131]. The latter one could lead to reduced cost for utility ratepayers and prolong the usage of existing infrastructure while maximising its utilisation factor.

Power quality issues due to stochastic generation and load are becoming increasingly important, as discussed in the Sections 1.1.1 and 1.1.2. The mentioned power quality issues (voltage unbalance, voltage variations, harmonic distortion, and flicker) can be successfully managed with BESS-s as discussed in Refs. [123, 139, 140]. Especially important power quality issues are the transient voltage variations and harmonic distortion of the network voltage due to the frequent starting and stopping of distributed generation as discussed in Refs. [98, 132]. Authors in Refs. [133, 135] bring out that a variety of power quality issues in microgrids (i.e., element failures, voltage swells and sags with short transients and high frequencies) are ideal to be met by energy storages with high ramping capability. Authors in Ref. [134] introduce a hybrid energy storage system that includes in addition to a battery also superconducting magnetic energy storage to compensate long and short-term voltage fluctuations to extend the lifetime of the battery. Authors in Refs. [136, 137] give a comprehensive overview about research regarding energy storage capabilities and summarise that an energy storage system can cope with most of the possible power quality-related issues. Ref. [138] summarised that voltage quality improvements are complementary otherwise to the load shifting application performed by the energy storage system.

The following table (Table 5) adopted from Ref. [110] and modified according to ENTSO-E and European Union terminology summarises the novel ancillary services that could be delivered with battery energy storages to different target groups.

3.3 | Application of grid scale BESS in different countries

In the 2020 ENTSO-E carried out a survey on ancillary services procurement and electricity balancing market design

TABLE 5 Battery enabled additional ancillary services in the future, their definitions, target groups, and coverage in scientific literature.

Service name	Definition	Target group	Papers
Resource and reserves Adequacies	Incrementally defer or postpone investments in peak load capacities on inertia reserves by utilising (battery) energy storage assets.	System operators, utility companies	[101–109]
Distribution/Transmission system adequacy	Incrementally defer or postpone investments in grid to meet peak load capacities by utilising (battery) energy storage assets.	System operators	[127, 129–131]
Transmission/Distribution congestion relief	Utilisation of (battery) energy storages to minimise the congestion on transmission/distribution lines during congestion hours	System operators	[100, 124–128]
Power quality services	Power quality maintenance and backup power for electricity consumers.	Electricity consumers	[98, 132–139].

amongst TSOs [141]. 47 countries (53 TSOs) were involved in the survey, and 30 (33 TSOs) of them provided answers. The TSOs were asked to answer questions of five topics: imbalance settlement, ancillary services, demand-side response, voltage control and black start. From the survey, we see that ancillary services are provided mainly via five assets: generators, demand-side response, pump storage, distributed generation, and batteries. The following table (Table 6) summarises the analysis regarding ancillary services and possibilities to provide it with BESS assets.

It should be noted that countries who stated that "All possible options" are accepted for different frequency regulation services were considered to accept services also from BESS units. Italy also stated in the survey that one significant/important change that is being implemented regarding the ancillary services is to involve low-consumption resources such as batteries coupled with PV in the ancillary services provision.

Regarding voltage control all the answered TSOs (100% from the ancillary services group) and additionally Luxembourg considers voltage control as an ancillary service. Only three TSOs (Finland, Germany, and Slovakia) consider storages as voltage control service providers. Since the survey does not specify the types of storages it consider, the authors assume that it also includes BESS. Other parts of the survey did not cover storages as assets for services.

Although ancillary services are a vital part of services that could be provided with BESS-s the future outlook forecasts that by 2030 the global grid-related annual deployment of energy storages will be focusing on capacity management, energy shifting, transmission and distribution management, and PV-s combined with storage applications in various sectors [142].

4 | CASE STUDY: BALTIC REGION DSOS

Increased integration of BESSs into distribution systems requires amendments to Grid Codes and Electricity Market Acts (EMA) to ensure their safe and fair operation. To identify possible issues and improvements into existing regulations, a case study was conducted among three Baltic DSOs: Elektrilevi OÜ of Estonia, AS Sadales tīkls of Latvia and Ignitis Group of Lithuania. The study was conducted during autumn 2021 and winter of 2021/2022.

The study was carried out in the form of an interview with Elektrilevi OÜ and in the form of e-mail exchange with AS Sadales tīkls and Ignitis Group. The interviewees of Elektrilevi OÜ were the Head of Market Relations and the Head of Technology. The method of the interview was semi-structured, where the discussed topics were known to the interviewees beforehand, and the interview results were followed up with internal discussions and manifested in a structured and reviewed interview protocol document. The interview was carried out in the national language to avoid miscommunication regarding legal and technical terms. The e-mail survey was composed of eight questions, some of which were complemented by one to three follow-up questions (a total of 20 individual questions). The communication with AS Sadales tīkls was relayed through Riga Technical University, who also provided relevant translations of their responses. The communication with Ignitis Group was conducted with their Head of Innovation and carried out in English.

The study focused mainly on two aspects regarding behind the metre energy storage systems: regulatory and technical. A summary of the DSO responses is provided in Table 7. All Baltic DSOs stated that they are not allowed to own or operate ESSs, which will change when the current EMA amendment draft enters into force. The EMA draft amendment states that grid operators can own, develop, manage, and operate ESSs when they are considered as fully integrated grid components, or they are required to enable efficient, reliable, and safe operation of the grid and not used for buying or selling electricity. The aim is to clearly separate grid operations form other processes involving ESSs, which is a similar approach as used for distributed generation. The described approach emphasises the involvement of private capital, rather than relying on strategic National investments for the large-scale integration of ESSs into the power grid.

All DSOs stated that they are currently unable to procure ancillary grid services. The reasons for this are limitations in regulations and the lack of service providers. However, the Lithuanian DSO has indicated that they are currently working towards a set of flexibility procurement rules, while the Estonian DSO has suggested that they support an exception to the grid tariff structure, where such ESS that are used to provide ancillary grid services are excluded from (some) tariffs. Matters become complicated when the purpose of the ESSs is not fixed to either energy management or network services, for example, mixed generation, load and storage assets

TABLE 6 List of countries who accept ancillary services (mainly frequency related) amongst other assets also from batteries.

	Frequency containment reserve		Frequency restoration reserve (automatic)		Frequency restoration reserve (manual)		Replacement reserve	
	Capacity	Energy	Capacity	Energy	Capacity	Energy	Capacity	Energy
All possible options	Belgium, France, Germany, Netherlands, Switzerland	France	Belgium, France, Germany, Netherlands, Switzerland, Slovenia	Belgium, France, Germany, Netherlands, Switzerland, Slovenia	Belgium, France, Germany, Netherlands, Switzerland, Slovenia	Belgium, Estonia, France, Germany, Italy, Netherlands, Switzerland, Slovenia	France, Switzerland	France, Italy. Switzerland
Generators + batteries	Austria, Czech Republic, Hungary	–	–	–	–	–	–	–
Generators + demand-side response + batteries	Denmark, Sweden, Finland	Sweden	Czech Republic	Czech Republic	–	–	–	–
Generators + demand-side response + pump storage + batteries	Ireland, Northern-Ireland	Ireland, Northern-Ireland	–	–	Czech Republic, Ireland, Northern-Ireland	Czech Republic, Ireland, Northern-Ireland	Ireland, Northern-Ireland	Czech Republic, Ireland, Northern-Ireland
Generators + batteries + distributed generation	–	–	Hungary	Hungary	Hungary	Hungary	–	–

TABLE 7 Summary of survey results carried out among Baltic DSOs.

Category	Estonia	Latvia	Lithuania
DSOs and ESS ownership	The EMA amendment draft states that grid operators can own, develop, manage, and operate ESSs when they are considered as fully integrated grid components, or necessary to enable efficient, reliable, and safe operation of the grid and not used for buying or selling electricity	Existing legislation prohibits DSO to operate and maintain EES for their own needs. A draft EMA amendment provides DSOs the possibility to own and operate ESS with permission of the regulating body.	Current legislation prohibits DSOs to own, develop, or operate energy storage facilities. There is an exception, which allows for DSOs to own ESSs in cases where they can be considered as an integrated grid component.
Grid connection requirements for ESSs	When a storage unit is behind a single inverter, the technical specifications are solved through manufacturer requirements. Most technical aspects regarding ESS integration to the grid are derived from the requirements identified for generators.	Current connection regulations of the Public Utilities Commission (PUC) do not separate or stipulate the connection process of EESs from producers and consumers. It is considered that since EESs are inverter-based generation units, the connection requirements must be similar to (micro)generation units. Therefore, the EES connection process depends on generation capacity.	ESSs are treated as generators and their functionality and protection requirements are same as for PV systems. The connection of ESSs is handled case-by-case. The technical connection conditions should include capacity (consumption and generation), while relevant technical characteristics of should meet generator grid code requirements (e.g., frequency and voltage protection, ramp rates, remote control, reactive power support etc.)
Grid tariffs for stored energy	Although network charges do not apply for produced energy, there is a separate statement in the draft EMA amendment regarding stored energy: no network charge is applied when returning stored energy to the network. This clause is aligned with the current situation, where distribution fees do not apply for generated electricity.	No special distribution tariff for ESS charging and discharging cycles and no actual plans to create such tariffs. The Latvian DSO supports the opinion that customers who offer the DSO services through ESSs must be proportionally remunerated for their services.	No special grid tariffs for providing energy to the grid from ESSs.
Perspective and planned changes in grid tariffs	The Estonian DSO suggests transitioning from mostly energy-based network charges to more capacity-based network charges, resulting in a larger revenue base from grid availability.	The Latvian DSO states that it is exploring a new tariff structure. Due to the reduction in distributed electricity (due to increased distributed generation), it is likely that the new tariff structure will have the fixed (capacity) component with a higher weight than the variable (electricity) component.	The Lithuanian DSO indicates that there is an ongoing study aiming to provide regulatory guidelines, including recommendations for grid tariffs, for the regulating body.

installed behind the metre. Additionally, there is a consensus of vision among Baltic DSOs, where they see a transition from mostly energy-based network charges to more capacity-based network charges, resulting in a larger revenue base from grid availability.

In terms of technical aspects, the integration process of ESSs into the power grid is currently analogous to electricity producers. Most technical aspects regarding ESS integration to the grid are derived from the requirements identified for generators. Although it is a resource efficient approach, it is recommended to state separate technical procedures and requirements for the integration of ESSs into the larger grid to account for the full extent of their flexibility. Additionally, the Estonian DSO recognises that it is possible that there are less sophisticated solutions currently connected to the grid that the DSO is unaware of and that for the differentiation of ESSs, they propose four options, which are based on:

a) capacity – similar to classifying (distributed) generators;
b) purpose – identify the use of the ESS, for example, strictly for influencing behind-the metre assets, energy trading, provision of network services, etc.;
c) control – which control functions are required from the perspective of the grid and the device;
d) dimensioning of protection equipment – what is the size of the necessary relay protection equipment required by the ESS.

5 | CONCLUSION

With the rapid development of technology, union policies with incentives, and a corresponding decrease of low carbon technology prices, more consumers connect PVs, BESSs, and EVs to the low voltage distribution grids. With the required infrastructure for public EV charging and demand-side management activities, the challenges for the system operators increase. The stochastic nature of the weather-impacted generation and new stochastic loads (e.g., EV charging) introduces challenges in voltage control and power quality assurance. The distribution grid needs to cope with bidirectional power flows and possibly amplified issues related to poor power quality caused by the scheduling of stochastic (and possibly non-linear) loads. Although PV systems can help mitigate some voltage magnitude and unbalance issues, the untimely scheduling of non-linear loads can cancel those effects. Grid stability can be affected by the large-scale utilisation of renewable energy sources because there are fluctuations in generation and load. These issues can be effectively addressed by grid-scale battery energy storage systems (BESS), which can respond quickly and provide high energy density which were thoroughly discussed in this paper.

Despite the fact that Battery Energy Storage Systems (BESS) offer effective solutions for managing power quality issues in the grid, their operation can also introduce harmonics. This incident occurs as a result of BESS' connection to the grid through inverters using Pulse Width Modulation (PWM). While BESS can reduce voltage fluctuations and improve power factor, PWM-based inverters can inadvertently generate harmonics, which can negatively affect grid power quality. Therefore, harmonic mitigation strategies must be carefully considered to minimise adverse effects when integrating BESS.

A case study was carries out in to analyse impacts of grid scale BESS on the Baltic DSOs and possible requirements to change their grid code. To summarise the survey case study results, the following conclusions can be drawn.

- Baltic DSOs will have the possibility to own and operate ESSs in case they can be considered as fully integrated grid components.
- Currently, there are no dedicated requirements for connecting ESSs to the grid and requirements for generators are commonly applied.
- Currently, there is no standard procedure for connecting ESSs to the grid and they are handled case-by-case, but procedures similar to connecting PV inverters to the grid are envisaged by the DSOs for the future.
- No special tariff or exemption is neither applied nor planned by the Baltic DSOs for stored energy.
- All DSOs have shown interest in using ESSs for grid services and the procurement of such services from respective service providers. As grid services are not supported by current legislation, the specific application of such mechanisms remains to be determined.
- It is deemed likely that current grid tariffs in the Baltic States are subject to change, mainly to adjust to the decrease in distributed energy and increase in distributed generation.

AUTHOR CONTRIBUTIONS

Freddy Plaum: Data curation; investigation. **Tobias Haring**: Formal analysis; investigation. **Imre Drovtar**: Investigation; methodology. **Tarmo Korotko**: Formal analysis; funding acquisition. **Argo Rosin**: Data curation; investigation.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

No sensitive data used.

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