

DOCTORAL THESIS

Aggregation and
Coordination of Residential
Demand-Side Flexibility for
Balancing Markets and Active
Distribution Networks

Arqum Shahid

TALLINN UNIVERSITY OF TECHNOLOGY
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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.

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**Kodumajapidamiste nõudluspoolse
paindlikkuse agregeerimine ja
koordineerimine tasakaalustamisturgudel
ning aktiivsetes jaotusvõrkudes**

ARQUM SHAHID



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List of Publications

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

- I. **Shahid, A.;** Ahmadiyahangar, R.; Rosin, A.; Blinov, A.; Vinnikov, D.; "Leveraging Machine-Learning Techniques for Demand-Side Flexibility—A Comprehensive Review," *Electric Power Systems Research*, 2024.
- II. **Shahid, A.;** Plaum, F.; Korötko, T.; Rosin, A.; "AI Technologies and Their Applications in Small-Scale Electric Power Systems," *IEEE Access*, 2024.
- III. **Shahid, A.;** Ahmadiyahangar, R.; Kilter, J.; Rosin, A.; "Data-Driven Quantification and Aggregation of Demand-Side Flexibility for Symmetrical Bidding in Energy Balancing Markets," *Electric Power Systems Research*, 2025.
- IV. **Shahid, A.;** Ahmadiyahangar, R.; Korötko, T.; Rosin, A.; "Transfer Learning-Based Aggregated Flexibility Forecasting for Participation in Local Energy Markets," *Proc. IEEE CCNCPS*, 2025.
- V. **Shahid, A.;** Ahmadiyahangar, R.; Rosin, A.; Korötko, T.; "Forecasting Demand-Side Flexibility of a Household with Dynamic Consumer Behaviour Analysis," *Proc. IEEE PES ISGT Europe*, 2024.
- VI. **Shahid, A.;** Rosin, A.; Ahmadiyahangar, R.; Korötko, T.; "Load Rebound Effect in Demand-Side Flexibility: Analyzing the Impacts on Grid Stability," *Proc. IEEE PSET*, 2025.
- VII. **Shahid, A.;** Ahmadiyahangar, R.; Rosin, A.; Maask, V.; Martins, J.; "Exploratory Data Analysis for Demand-Side Flexibility Quantification," *Proc. IEEE CPE*, 2023, doi: 10.1109/CPE-POWERENG58103.2023.10227408.
- VIII. **Shahid, A.;** Ahmadiyahangar, R.; Rosin, A.; Korötko, T.; "Integrating BRP and Aggregator Roles for Imbalance Management and Frequency Regulation Using Demand-Side Flexibility," *IEEE GreenTech*, 2026.
- IX. **Shahid, A.;** Korötko, T.; Rosin, A.; Ahmadiyahangar, R.; Plaum, F.; "Deep Reinforcement Learning-Based Model-Free Voltage Regulation in an Energy Community Using Demand-Side Flexibility Aggregation," *Electric Power Systems Research*, under review.
- X. **Shahid, A.;** Ahmadiyahangar, R.; Rosin, A.; Shabbir, N.; "Forecast-Driven Aggregation and Real-Time Coordination of Demand-Side Flexibility for Balancing Market Participation," *IEEE Access*.

Author's Contribution to the Publications

The author's contributions to the papers in this thesis are:

- I. Arqum Shahid, as the main author, conducted a comprehensive literature review on machine-learning techniques for demand-side flexibility, establishing the conceptual and methodological foundation for flexibility characterization, forecasting, and control in this thesis.
- II. Arqum Shahid, as the main author, reviewed AI technologies for small-scale power systems, providing the broader technological context and identifying the role of AI in enabling data-driven flexibility management.
- III. Arqum Shahid, as the main author, developed the data-driven flexibility quantification and aggregation methodology, forming the core basis for modeling residential flexibility and constructing market-compliant reserve capacity in this thesis.
- IV. Arqum Shahid, as the main author, proposed the transfer learning-based aggregated flexibility forecasting approach, contributing to scalable community-level flexibility estimation under data-scarce conditions.
- V. Arqum Shahid, as the main author, developed household-level flexibility forecasting considering dynamic consumer behavior, supporting the understanding of variability and uncertainty in residential flexibility.
- VI. Arqum Shahid, as the main author, analyzed the load rebound effect in demand-side flexibility, highlighting its impact on grid stability and its implications for reliable flexibility deployment.
- VII. Arqum Shahid, as the main author, performed exploratory data analysis for flexibility quantification, supporting feature extraction and data-driven modeling of residential flexibility.
- VIII. Arqum Shahid, as the main author, developed the integrated BRP-aggregator framework for imbalance management and frequency regulation, linking flexibility utilization to economic and market operation aspects.
- IX. Arqum Shahid, as the main author, proposed the deep reinforcement learning-based model-free voltage regulation framework, contributing to distribution-level control using aggregated demand-side flexibility.
- X. Arqum Shahid, as the main author, developed the forecast-driven aggregation and real-time coordination framework, demonstrating end-to-end market participation and operational validation of residential flexibility.

Abbreviations

ADN	Active Distribution Network
aFRR	automatic Frequency Restoration Reserve
AI	Artificial Intelligence
ANN	Artificial Neural Network
BESS	Battery Energy Storage System
Bi-LSTM	Bidirectional Long Short-Term Memory
BRP	Balance Responsible Party
BSP	Balancing Service Provider
CNN	Convolutional Neural Network
CTDE	Centralized Training with Distributed Execution
CVaR	Conditional Value at Risk
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DDPG	Deep Deterministic Policy Gradient
DER	Distributed Energy Resources
DHW	Domestic Hot Water
DRL	Deep Reinforcement Learning
DSF	Demand-Side Flexibility
DSO	Distribution System Operator
DW	Dishwasher
EBGL	Electricity Balancing Guideline
EV	Electric Vehicle
FCR	Frequency Containment Reserve
FCR-D	Frequency Containment Reserve for Disturbances
FCR-N	Frequency Containment Reserve for Normal operation
FP-Growth	Frequent Pattern Growth
GRU	Gated Recurrent Unit
HEMS	Home Energy Management System
HIL	Hardware-in-the-Loop
HVAC	Heating, Ventilation, and Air Conditioning
LSTM	Long Short-Term Memory
MADRL	Multi-Agent Deep Reinforcement Learning
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
mFRR	manual Frequency Restoration Reserve
MILP	Mixed-Integer Linear Programming
MIMF-NN	Multi-Input Multi-Feature Neural Network
ML	Machine Learning
MPC	Model Predictive Control
MTU	Market Time Unit
NILM	Non-Intrusive Load Monitoring
NRMSE	Normalized Root Mean Square Error
OLTC	On-Load Tap Changer
PCA	Principal Component Analysis
PCC	Point of Common Coupling
PPO	Proximal Policy Optimization

PV	Photovoltaic
QP	Quadratic Programming
RES	Renewable Energy Sources
RF	Random Forest
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RTDS	Real-Time Digital Simulator
SAC	Soft Actor-Critic
SoC	State of Charge
SVM	Support Vector Machine
TCL	Thermostatically Controlled Load
TD3	Twin Delayed DDPG
TL	Transfer Learning
TSO	Transmission System Operator
V2G	Vehicle-to-Grid
XGBoost	Extreme Gradient Boosting

Symbols

Symbol	Description	Unit
P	Active power	kW, MW
Q	Reactive power	kVAr
E	Energy	kWh
Δt	Time interval	s, min
f	System frequency	Hz
Δf	Frequency deviation	Hz
ΔV	Voltage deviation	p.u.
$P^\uparrow, P^\downarrow$	Upward and downward flexibility	kW
$E^\uparrow, E^\downarrow$	Upward and downward energy flexibility	kWh
P_{flex}	Available flexible power	kW
E_{flex}	Available flexible energy	kWh
R	Reserve capacity (e.g., FCR)	kW, MW
P_{base}	Baseline power consumption	kW
P_{act}	Activated power	kW
ΔP	Power deviation from baseline	kW
r	Ramp rate	kW/s
SoC	State of Charge (battery)	%
$SoC_{\text{min}}, SoC_{\text{max}}$	Minimum and maximum state of charge	%
η	Efficiency (e.g., battery or system)	—
λ	Electricity price / market signal	€/MWh
C	Cost function	€
π	Imbalance penalty price	€/MWh
$\hat{P}$	Forecasted power/flexibility	kW
ϵ	Forecast error	—
$\mathbb{E}[\cdot]$	Expected value	—
u	Control/input variable	—
a	Action (in DRL framework)	—
s	State (in DRL framework)	—
r_t	Reward at time t	—
γ	Discount factor	—
θ	Model parameters / weights	—
$\mathcal{L}$	Loss function	—
N	Number of households/resources	—
i	Index of household/resource	—

1 Introduction

1.1 Background

“There is no ‘Plan B’ for actions because we do not have ‘Planet B’.”

This statement, delivered by former United Nations Secretary-General Ban Ki-moon at the 2014 Climate Summit, remains highly relevant to the contemporary energy transition [1]. It captures the urgency of global climate action and the need for coordinated measures to mitigate the accelerating impacts of climate change. Although major policy progress has been achieved over the past decade, most notably through the Paris Agreement adopted in 2016, the international community remains behind its intended decarbonization trajectory. Within this global context, the European Union (EU) has positioned itself as a frontrunner by committing to becoming the first climate-neutral continent by 2050 [2]. Achieving this objective requires a fundamental restructuring of the energy sector, which remains one of the main contributors to greenhouse gas emissions and accounted for 27.4% of total EU emissions in 2023 [3].

The decarbonization process is shifting electricity systems from centralized, unidirectional grids to decentralized, dynamic networks integrated with renewable energy sources (RES) and distributed energy resources (DERs) [4]. By 2024, renewables contributed 46.9% of net electricity generation in the EU, with wind and solar representing the dominant share. Although this transition is essential for reducing carbon emissions, it also introduces several technical and operational challenges [5].

A key operational challenge in low-inertia power systems is the increasing sensitivity of system frequency to short-term imbalances between generation and demand. As inverter-based renewable generation replaces synchronous generation, frequency deviations can occur more rapidly and require faster corrective action. This increases the importance of fast frequency response products, particularly frequency containment reserves, such as Frequency Containment Reserve for Normal operations (FCR-N), which require symmetric active-power capacity and reliable dynamic delivery after activation. Residential demand-side flexibility, when aggregated and coordinated, can contribute to this type of service by adjusting controllable loads and behind-the-meter storage in response to frequency deviations [6].

In parallel, distribution networks face local voltage-control challenges due to rooftop PV, EV charging, heat pumps, and bidirectional power flows [7]. Conventional voltage regulation apparatuses, such as on-load tap changers (OLTCs) and capacitor banks, are not designed for such dynamic and distributed contexts. The active distribution network (ADN) concept emerges as a solution, leveraging automation and control to coordinate DERs, effectively evolving distribution grids into cyber-physical systems requiring proactive management. Voltage regulation in ADNs increasingly depends on the coordinated response of distributed flexible assets, which can adjust local consumption or injection to maintain acceptable voltage profiles across feeders [8].

Within this evolving landscape, demand-side flexibility (DSF) has emerged as a pivotal enabler of both technical stability and market efficiency, allowing consumers to modulate energy usage in response to external signals [9]. It complements utility-scale storage and conventional reserves, supporting the operational frameworks of balancing responsible parties (BRPs) and aggregators [10]. While DSF has traditionally been sourced from industrial and commercial sectors, the proliferation of DERs has unlocked

substantial potential at the residential level, a sector that accounted for 25.9% of total EU electricity consumption in 2023 [11].

European regulatory reforms have further strengthened the institutional basis for activating this flexibility. The Clean Energy Package, including Directive (EU) 2019/944 and Regulations (EU) 2019/943 and 2024/1747, promotes consumer-centered electricity markets and non-discriminatory participation of demand response and aggregation. These reforms clarify the role of independent aggregators and facilitate the participation of distributed resources in day-ahead, intraday, and balancing markets. In this framework, TSOs access flexibility through market mechanisms, whereas DSOs ensure that their activation remains compatible with local network security and power quality [12].

Nevertheless, unlocking residential flexibility at scale remains challenging. Residential resources are small, dispersed, behavior-dependent, and constrained by appliance dynamics, user comfort, and local network limitations. Their effective integration, therefore, requires accurate quantification, robust aggregation, and real-time coordination across multiple temporal and spatial levels. Smart meters, telemetry, cloud platforms, and edge controllers provide the observability and controllability necessary to manage flexible resources. While artificial intelligence (AI) and machine learning (ML) offer proven capabilities for forecasting, scheduling, and microgrid control [Paper I], [Paper II], existing studies predominantly address flexibility quantification, bidding, and real-time coordination in isolation, leaving only a weak connection between flexibility characterization, market participation, and physical service delivery. This fragmentation, compounded by data scarcity and the non-linear behavior of residential resources, limits the reliable translation of residential portfolios into fast ancillary and local grid-support services. As a result, a clear research gap exists in the lack of an integrated framework that can coherently link these interdependent functions into a unified operational pipeline. Therefore, the transition toward a decarbonized and resilient energy system requires systematic approaches for quantifying, aggregating, coordinating, and monetizing flexibility across technical, market, and distribution-level domains.

1.2 Scope of flexibility services

This thesis uses residential demand-side flexibility for two distinct grid-service applications. The first and primary market-facing application is FCR-N reserve provision. In this context, **reserve** refers to the symmetric active-power capacity committed by the aggregator before activation, while **response** refers to the real-time active-power modulation delivered after a frequency deviation. **Energy** refers only to the quantity delivered or absorbed during activation and to the resulting imbalance settlement effects; it is not treated as the main market product. The second application is voltage regulation in active distribution networks, where the same type of active-power flexibility is used as a local grid-support service for DSOs. These two applications are related through the common flexibility resource base but represent different service products and operational contexts.

1.3 Motivation

The ongoing transition from synchronous generation to inverter-based renewable energy resources is reducing system inertia and increasing the vulnerability of modern

power systems to frequency deviations and voltage instability. These challenges are particularly significant in ADNs, where the rapid growth of DERs, EVs, heat pumps, and rooftop PV systems has introduced highly dynamic and uncertain operating conditions. In this context, residential DSF offers considerable yet still underutilized potential to support both system-level frequency regulation and local voltage control.

Despite this potential, the practical integration of residential DSF into ancillary service provision remains constrained by several key challenges.

- First, its deployment requires robust flexibility quantification methods capable of capturing appliance-level dynamics, operational constraints, and variations in consumer behavior.
- Second, aggregators require accurate and scalable forecasting models to estimate community-level flexibility availability under data scarcity.
- Third, forecasted flexibility must be transformed into feasible and market-compliant aggregation strategies, including risk-aware disaggregation mechanisms that allocate flexibility to individual resources while minimizing user discomfort.
- Fourth, real-time coordination frameworks are necessary to ensure that committed flexibility can be delivered reliably during service activation and changing grid conditions.

Therefore, this thesis is motivated by the need to develop an integrated framework for the quantification, forecasting, aggregation, disaggregation, and real-time coordination of residential DSF for effective participation in frequency and voltage regulation services. In addition, such an integrated approach enables economic value creation for aggregators, BRPs, and system operators by unlocking new revenue streams from ancillary service markets, reducing imbalance costs, and improving the overall cost-efficiency of grid operation.

1.4 Aim, Hypothesis, and Research Tasks

The main aim of this thesis is to develop and validate a comprehensive framework for the effective utilization of residential flexibility to provide dual grid services: frequency regulation through balancing market participation and voltage control in ADNs. The study establishes a methodology covering data-driven flexibility quantification, forecast-driven aggregation, and real-time resource coordination, supported by optimization methods and RTDS-based validation for market-compliant aggregator participation.

Hypotheses:

1. The application of data-driven dynamic comfort zone modeling to residential appliance-level flexibility quantification and aggregation enables the formation of symmetrical FCR-N reserve capacity that consistently meets or exceeds the minimum balancing market bid threshold while maintaining user discomfort within learned comfort limits.
2. Utilizing a transfer learning-based forecasting model that learns from a representative subset of households selected via behavioral clustering, yields higher predictive accuracy for community-level flexibility compared to single-aggregate forecasting models under data-scarce conditions.
3. A forecast-driven market participation framework incorporating appliance dynamics combined with risk-aware hierarchical disaggregation reduces

flexibility under-delivery and improves the feasibility of residential aggregator bids compared with proportional or non-risk-aware allocation methods.

4. Real-time coordination of residential flexibility resources with BESS to compensate for slower-responding resources enables residential aggregators to maintain the aggregate portfolio's mean absolute tracking error within the balancing-market dynamic performance limits despite uncertainty in appliance availability, user behaviour, and operating conditions.
5. A coordinated BRP-aggregator strategy can create positive net value by combining FCR-N reserve revenues with imbalance-cost management.
6. In active distribution networks, a deep reinforcement learning-based coordinator agent employing implicit sensitivity learning and adaptive droop mapping achieves targeted local voltage regulation and reduces on-load tap changer operations more effectively than a fixed capacity-proportional allocation policy.

Research Tasks:

1. Systematic analysis of demand-side flexibility definitions, multi-vector resource characteristics, and aggregation architectures to establish a unified conceptual framework and identify technical gaps in current residential flexibility quantification and market-integrated operations (Chapter 2).
2. Development of a data-driven quantification and aggregation methodology to map heterogeneous multi-vector residential assets into dynamic, comfort-dependent operating regions, enabling the formation of symmetrical reserve capacity that respects user-defined comfort boundaries (Chapter 3).
3. Development of a market participation optimization framework incorporating transfer learning-based forecasting architecture, dynamic capability mapping and risk-aware hierarchical disaggregation to translate steady-state flexibility forecasts into FCR-N compliant bids with minimized under-delivery risk and user discomfort (Chapter 4).
4. Development of a real-time coordination mechanism for multi-vector residential flexibility resources with BESS compensation to maintain aggregate portfolio tracking performance within balancing market dynamic limits during frequency activation events (Chapter 4).
5. Formulation of a unified BRP-Aggregator economic optimization model to quantify and manage the systemic trade-offs between internal imbalance cost minimization and external revenue generation from frequency regulation markets (Chapter 4).
6. Development of a model-free multi-agent deep reinforcement learning framework for voltage regulation in active distribution networks using only active-power flexibility to learn implicit voltage-power sensitivities without requiring network topology or line parameters (Chapter 5).

1.5 Contribution and Dissemination

This research advances the state of the art in residential demand-side flexibility by developing end-to-end methods that transform heterogeneous, comfort-constrained household resources into reliable grid services. The work contributes a unified methodological pathway spanning data-driven flexibility quantification and aggregation, community-level forecasting under limited data, market participation-window selection

with risk-aware disaggregation, and real-time coordination and control, all validated in closed-loop operation using real-time digital simulation. Collectively, the results demonstrate how residential portfolios can be operationalized for both frequency regulation, via frequency containment reserve for normal operation (FCR-N) participation, and voltage regulation in active distribution networks.

The results of this thesis have been disseminated within academic and professional communities. Key findings have been presented at five international conferences and published in 3 peer-reviewed journals, ensuring that the methodology and insights are accessible to a wider audience. The core contributions of this thesis are categorized into theoretical advancements and practical implementations:

Scientific Novelties:

- **Dynamic Operating Region Characterization:** Development of a novel data-driven flexibility quantification methodology that employs machine learning techniques to learn user behavior patterns and map heterogeneous multi-vector residential resources into dynamic, comfort-dependent operating regions that evolve with changing user preferences.
- **Generalization via Transfer Learning (TL):** A novel Multi-Input Multi-Feature Neural Network (MIMF-NN) based transfer learning strategy is introduced to generalize forecasting knowledge from representative households, identified through PCA and K-means, to the wider residential community using data from as few as 17% of total households, thereby addressing the limited target-domain data problem that commonly restricts newly formed aggregator portfolios.
- **Dynamic Capability Mapping for Market-Compliant Reserve Formation:** Introduction of a methodology that translates steady-state flexibility forecasts into dynamically deliverable capacity caps by incorporating first-order and second-order device response models that respect the physical ramping limitations of HVAC, BESS, and shiftable loads. This mapping is embedded within the market participation optimization, ensuring compliance with stringent FCR-N activation timelines.
- **Risk-Aware Hierarchical Disaggregation:** Formulation of a new two-stage flexibility disaggregation strategy employing availability-weighted driver-energy quantiles, CVaR-lite caps, and eligibility gating to allocate aggregated commitments to individual households while explicitly quantifying and limiting exposure to volatile resources, significantly reducing fleet-level under-delivery risk from intermittent resources.
- **Model-Free Multi-Agent DRL Framework:** Development of a novel framework for voltage regulation in active distribution networks that utilizes CTDE hierarchical architecture with SAC-DRL agents that learns implicit voltage-power sensitivities through interaction, enabling real-time voltage regulation using only active-power flexibility without requiring network topology, line parameters, or explicit grid models while significantly reducing OLTC operations.

Practical Novelties:

1. For Residential Aggregators and Independent Flexibility Providers:

- Demonstration of a complete market participation operational chain from data-driven quantification through real-time coordination, validated in closed-loop RTDS experiments, enabling residential aggregators to provide symmetric FCR-N reserves exceeding the 0.1 MW minimum bid threshold with proven market compliance.
- Achievement of practical computational performance suitable for operational deployment, with the MILP-based market participation solving in approximately 0.9 seconds per window and real-time coordination requiring only 0.67 seconds per interval, enabling sub-second corrective actions during frequency activation events.
- Demonstration that the transfer learning approach achieves high forecasting accuracy using representative data from only 17% of households, addressing the critical barrier of data scarcity for new aggregators entering markets with limited historical telemetry.

2. For TSOs, DSOs, and BRPs

- Delivers RTDS-validated, model-free voltage regulation with improved compliance with the defined ± 10 V and ± 15 V operating bands while reducing OLTC tap operations by up to 73%, thereby extending maintenance intervals and lowering OPEX, and enabling DSOs to manage high-DER feeders without detailed network models or extensive observability.
- Provides residential frequency containment reserves capacity with proven dynamic performance during activation, achieving a coverage ratio of 1.033 and 96.9% energy delivery accuracy in the tested case, enabling residential consumers to offer TSOs a scalable fast-acting FCR-N reserve source to compensate for declining synchronous inertia.
- Demonstration of 4.75% net operational cost reduction through integrated dual-role operation, allowing BRPs to monetize community flexibility through FCR-N capacity and activation payments while strategically managing the trade-off between frequency-driven reserve activations and resulting imbalance penalty risks.

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1.6 Application

The accelerating deployment of inverter-based renewable generation is reshaping power-system operation by increasing variability and reducing the availability of synchronous inertia. Globally, renewable power capacity additions reached a record 585 GW in 2024, and renewables represented 92.5% of all net power capacity additions, with solar alone contributing 452 GW [13]. In parallel, the rapid expansion of distributed

photovoltaic generation, largely connected at the distribution level, has been substantial; global cumulative PV capacity grew to 1.6 TW in 2023, with 407 GW of new PV systems commissioned within that year [14]. These trends intensify both short-term frequency control challenges at the system level and voltage management challenges in active distribution networks, where bidirectional flows and highly time-varying net demand are increasingly common.

The outcomes of this thesis are directly applicable to these two high-impact operational needs in modern power systems: (1) enabling residential aggregators to deliver fast, symmetric frequency regulation services (with FCR-N used as the benchmark product), and (2) supporting DSOs in maintaining statutory voltage quality under high DER variability while reducing reliance on mechanical voltage control devices.

1.6.1 Application to balancing market participation by residential aggregators

The proposed framework can be deployed as an aggregator decision-and-control stack that spans the full operational chain from planning to activation. At the preparation stage, residential flexibility is quantified in a data-driven manner by learning user behavior and mapping device operation into dynamic comfort-dependent operating regions. These regions are aggregated across multiple residential vectors (e.g., thermostatically controlled loads, shiftable appliances, and battery storage) to form symmetric reserve envelopes suitable for frequency services. To support bidding and scheduling, community-level upward and downward flexibility is forecast using a multi-input, multi-feature neural model enhanced via transfer learning, which is particularly valuable when only limited historical data is available for new portfolios. Forecasts are then passed to a market-window optimization layer that selects feasible 15-minute participation intervals and produces market-compliant bids while enforcing device constraints and user comfort limits. This pipeline directly targets key FCR-N requirements, including symmetric capacity, 15-minute product structure, and stringent delivery performance following activation. A hierarchical, risk-aware disaggregation stage translates aggregate bids into feasible household-level setpoints while controlling under-delivery risk and limiting discomfort. During activation, a real-time coordination layer corrects forecast–delivery mismatches by reallocating setpoints based on current availability, while droop-based response provides second-level tracking needed for frequency regulation. In real-time simulation, the residential portfolio demonstrated a symmetric flexibility capability peaking at 130 kW, exceeding the typical 0.1 MW minimum bid threshold, indicating practical market relevance for community-scale aggregation.

From an economic perspective, the demonstrated 130 kW of symmetric reserve capacity can generate material revenue under current Nordic market conditions. With Fingrid’s 2025 yearly market FCR-N capacity price at 25.30 €/MW/h and activation energy compensated at the imbalance price, a 130 kW portfolio operating over a conservative 12-hour daily window could earn approximately €14,400 per year in capacity payments alone, with additional activation revenues during frequency deviation events [15], [16].

1.6.2 Model-free voltage regulation for DSOs.

The thesis further demonstrates that the same demand-side flexibility can serve as a fast voltage support actuator without requiring an explicit grid model. A centralized-training, distributed-execution (CTDE) hierarchical multi-agent DRL controller is proposed, where a coordinator agent converts measured voltage deviations into flexibility requests and bus-level agents disaggregate these requests into device actions. This model-free strategy is well-suited to distribution systems where topology and parameters are uncertain or time-varying. In RTDS closed-loop evaluation, the controller-maintained voltages within statutory bands while significantly reducing mechanical OLTC usage, supporting improved asset lifetime and operational efficiency. From an economic standpoint, the observed reduction of up to 73% in OLTC operations translates into lower maintenance costs, extended equipment lifetime, and deferred capital investment in network reinforcement. These operational benefits provide DSOs with a cost-effective alternative to traditional infrastructure upgrades, particularly in high-DER distribution networks.

Overall, the thesis provides deployable pathways for aggregators to participate in fast frequency services provision through quantification, forecasting, bidding, disaggregation, real-time coordination, and DSO-centric voltage regulation, using model-free, learning-based coordination of residential DSF to improve stability and reduce reliance on mechanical voltage control devices.

1.7 Thesis Outline

The thesis is structured into six main chapters. Chapter 2 introduces demand-side flexibility by defining the concept, summarizing its main residential sources, and reviewing how flexibility is characterized and utilized in existing ancillary service markets, including common AI-driven methods and evaluation metrics. Chapter 3 introduces a data-driven framework for quantifying demand-side flexibility from heterogeneous household appliances, considering dynamic user comfort. Chapter 4 develops a forecast-driven aggregation and real-time coordination strategy for balancing market participation. Chapter 5 presents a hierarchical, model-free deep reinforcement learning framework for real-time voltage regulation using aggregated flexibility. Finally, Chapter 6 concludes the thesis, and Chapter 7 outlines directions for future research.

2 State of the Art on Residential Demand-Side Flexibility

Residential demand-side flexibility (DSF) describes the ability of households to adjust electricity consumption and/or behind-the-meter injection in response to market signals or system-operator requests, often coordinated by aggregators [17]. DSF is increasingly valuable as inverter-interfaced renewable generation reduces effective inertia and shifts operational needs toward fast frequency stabilization and local voltage management. This chapter reviews (1) DSF definitions and techno-economic roles, (2) key residential flexibility sources and their control characteristics, (3) relevant balancing and ancillary service markets (including Nordic FCR-N and mFRR), (4) flexibility characterization and quantification methods, (5) AI-driven forecasting, aggregation/disaggregation, and control strategies, and (6) evaluation metrics for compliance, comfort, and network impact. The synthesis highlights persistent gaps, particularly the weak coupling between quantification, forecasting, bidding, and real-time coordination, and motivates an integrated end-to-end DSF framework grounded in the thesis papers and supporting literature.

2.1 Demand-side flexibility concept and roles

In European regulation, demand response is defined as the change of electricity load by final customers from their normal or current consumption patterns in response to market signals (including time-variable prices and incentive payments), or in response to acceptance of a bid in an organized market, either alone or through aggregation [18].

Within this framing, residential DSF can be interpreted as the subset of demand response that is technically feasible under device dynamics and network constraints, and behaviorally feasible under occupancy and comfort preferences, such that the response is repeatable and verifiable for market and grid services. According to the Smart Energy Demand Coalition [19], demand-side flexibility can be defined as:

‘The capacity to change electricity usage by end-use customers (including residential) from their normal or current consumption patterns in response to market signals, such as time-variable electricity prices or incentive payments, or in response to acceptance of the consumer’s bid, alone or through aggregation, to sell demand reduction/increase at a price in electricity markets or for internal portfolio optimization.’

Fig. 2.1 shows various response strategies and sources of demand-side flexibility [paper I]. On the strategy side, demand adjustment is achieved by either shifting usage to off-peak hours or reducing consumption during peak hours, implemented through manual response (consumer awareness and incentive programs) or automated response (smart meters and smart thermostats) [20]. On the asset side, flexibility originates from consumption adjustment of end-uses (electric vehicles, appliances, and heating/cooling systems), storage (batteries and thermal storage), and generation-side options, spanning distributed generation (e.g., gas/diesel units) and renewable sources (solar and wind) [21]. Technically, DSF supports power-system operation across multiple time-scales. At seconds-to-minutes resolution, it can contribute to frequency containment, supplementing governor-type response as synchronous inertia declines. At minutes-to-hours resolution, it can provide balancing energy (e.g., mFRR activation and intra-period corrections). In active distribution networks, DSF can also act as a local voltage-support actuator, which is particularly relevant in low-voltage feeders where voltage magnitude is often strongly sensitive to active-power changes due to high R/X ratios [22].

Economically, DSF creates value through (at least) three interconnected channels. First, it reduces net imbalance exposure by enabling portfolio corrections closer to real time, important for balance-responsible entities facing imbalance penalties [23]. Second, it generates ancillary-service revenue (capacity and/or energy payments), especially in services with stringent dynamic requirements and high value per MW [24]. Third, in distribution-level applications, DSF can reduce reliance on mechanical voltage regulation and defer network reinforcement, creating system-level value even when market remuneration is local or contractual rather than wholesale [25].

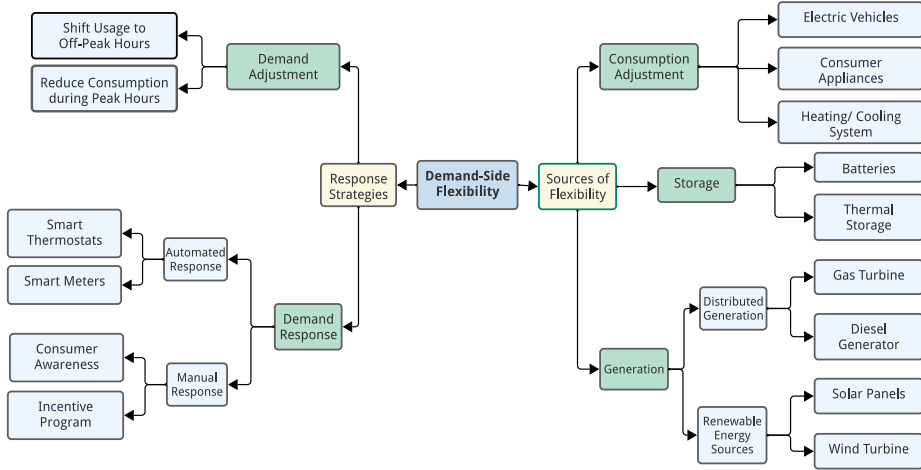


Figure 2.1. Overview of demand-side flexibility response strategies and their key sources [paper I]

2.2 Residential flexibility sources and control characteristics

DSF is inherently multi-vector and heterogeneous, arising from various devices that employ distinct storage mechanisms and control interfaces for user comfort. A typical residential DSF architecture, centered on a home energy management system (HEMS), integrates diverse flexible assets such as photovoltaic panels, battery energy storage systems, HVAC systems, and household appliances through smart plugs and gateways, as shown in Fig. 2.2 [paper I]. The HEMS enables data-driven operations by leveraging weather forecasts, demand predictions, real-time pricing, and user behavior patterns, facilitating flexibility quantification, control optimization, resource aggregation, and dispatch [26]. Flexible resources can be classified into three categories: (a) thermostatically controlled loads (TCLs) utilizing thermal inertia, (b) electrochemical storage, and (c) deferrable shiftable loads with defined scheduling windows.

- **HVAC / heat pumps (space heating and cooling):** These systems provide flexibility by leveraging building thermal inertia through set-point modulation and curtailment. While offering rapid actuation, their feasibility is constrained by thermal dynamics and occupant comfort needs [27].

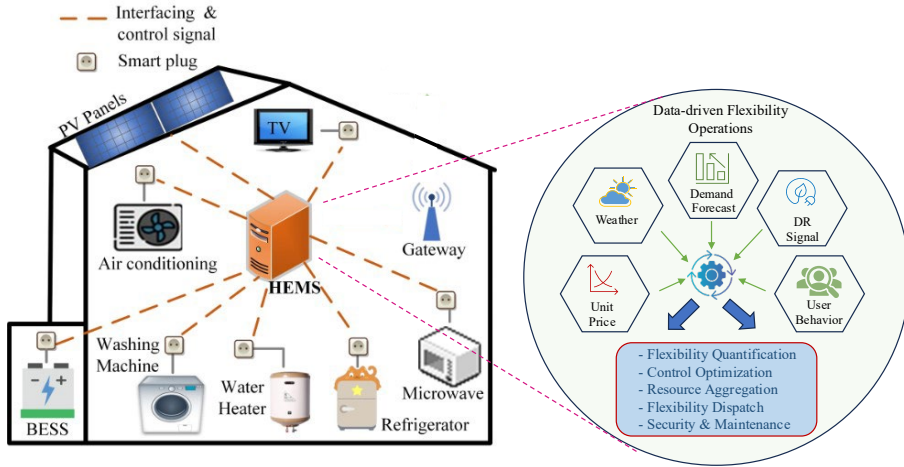


Figure 2.2. HEMS that enables coordinated residential flexibility [paper I].

Furthermore, post-activation demand rebound can trigger significant frequency excursions, necessitating behavior-aware control to maintain grid stability [28].

- **Domestic hot-water (DHW) heaters:** DHW heaters utilize tank thermal capacity as a flexible energy reservoir. While energy mapping is more straightforward than in HVAC systems, DHW availability is highly contingent on stochastic hot-water draw patterns, and user routine, requiring probabilistic modeling for reliable large-scale bidding [29].
- **Electric vehicles (EVs):** EV flexibility stems from deferred charging and bidirectional vehicle-to-grid (V2G) responses [30]. However, this flexibility is characterized by high variance due to behavioral factors, such as mobility patterns and plug-in probability. This uncertainty drives the need for community-level forecasting and risk-aware reserve assignment [31].
- **Behind-the-meter battery energy storage systems (BESS):** Residential BESS offers rapid, symmetric response but is constrained by inverter ratings, state-of-charge (SoC) limits, and degradation. In practice, BESS often complements thermostatically controlled loads (TCLs) in hybrid architectures, where batteries provide fast tracking precision and TCLs offer longer endurance [32].
- **Shiftable (deferrable) loads:** Appliances like dishwashers provide flexibility through start-time shifting within user-defined windows. While effective for scheduling and energy balancing, their discrete control and intermittent availability make them less suitable for continuous real-time frequency tracking.

A cross-cutting constraint for all demand-side flexibility (DSF) is occupant convenience. To ensure sustained participation and economic viability, DSF must be harvested strictly within established comfort and utility limits.

2.2.1 Flexibility characterization

Flexibility characterization formalizes “what can be changed, by how much, for how long, when, and at what cost/discomfort”. In residential DSF, this is difficult because feasibility is time-coupled (thermal/SoC states), behaviour-dependent (occupancy and routines), and market-conditioned (product definitions and symmetry). Fig. 2.3 illustrates the fundamental flexibility activation profile, decomposing the response into distinct temporal phases and quantifiable parameters that must be explicitly represented in any comprehensive characterization framework [paper I].

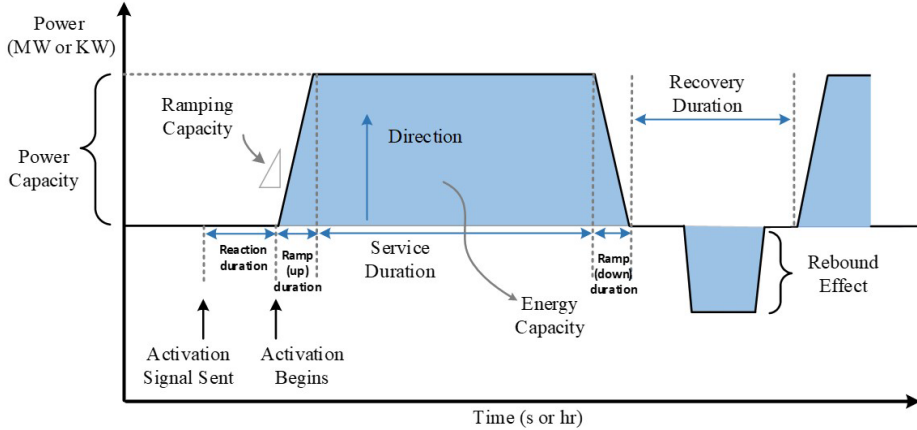


Figure 2.3. Characteristics of demand-side flexibility [paper I].

The activation profile reveals several critical dimensions that static indicators often fail to capture:

- Temporal Response Characteristics:** The interval between the *activation signal sent* and *activation begins* constitutes the **reaction duration** (or activation delay), representing communication latency and device response preparation time. This is followed by **ramp duration**—the time required to transition from baseline to full power capacity, which may differ between upward (*ramp-up*) and downward (*ramp-down*) activations. The **service duration** defines how long the full power capacity can be sustained before endurance limits or comfort constraints force restoration. Finally, the **recovery duration** captures the time required to return to normal operating conditions, during which the *rebound effect* may manifest as compensatory consumption that partially or fully offsets the initial energy reduction.
- Power and Energy Capabilities:** **Power capacity** (measured in MW or kW) represents the maximum available modulation magnitude above or below baseline, while **ramping capacity** indicates the achievable rate of power change (MW/min or kW/s). The **direction** of flexibility (upward or downward) indicates whether the service increases or decreases consumption relative to baseline. Critically, **energy capacity**—the integral of power over the service duration—determines the total energy that can be delivered or absorbed, distinguishing between *power-intensive* services (high power, short duration) and *energy-intensive* services (moderate power, extended duration).

- **Rebound Dynamics:** The rebound effect illustrated in the figure represents post-activation consumption behaviour where deferred loads resume operation, potentially creating secondary demand peaks that must be anticipated in scheduling and aggregation. This temporal coupling between activation and recovery phases means that flexibility quantification cannot treat individual activations as isolated events; rather, the complete cycle, including service delivery and rebound management, must be characterized as an integrated temporal sequence [paper VI].

2.3 Market context for residential DSF

The participation of residential flexibility in the European electricity markets spans wholesale, balancing, and ancillary services, alongside emerging distribution-level procurement. This integration is governed by the EU's Clean Energy for all Europeans Package, specifically Directive (EU) 2019/944, which establishes a "level playing field" for demand-side resources through aggregation [33]. Despite these regulatory foundations, residential portfolios face persistent market interface challenges, including bid granularity, activation timing, endurance limits, and rigorous performance verification (telemetry and baselining), which require sophisticated management via control algorithms [34].

A critical enabler for DSF is the increasing temporal granularity of European markets, notably the transition to 15-minute trading intervals within the Single Day-Ahead Coupling (SDAC). This shift allows flexible demand to more effectively monetize the rapid fluctuations of renewable generation and load. In Estonia, for instance, the TSO Elering has facilitated this transition by publishing national guidance on the implementation of 15-minute pricing and billing procedures [35].

2.3.1 Current ecosystem for flexibility provision via aggregators

A practical view of the flexibility ecosystem distinguishes commercial roles (who contract with the customer and trade energy) from system roles (who are responsible for balance and who deliver verified reserves):

- **Consumer-Facing Value Chain:** The Final Customer (Prosumer) provides controllable assets like EVs and batteries within specified comfort constraints, which the Aggregator bundles and optimizes. These aggregators may operate independently or be embedded within a retailer, serving as the central link that forecasts availability and manages device-level constraints to create tradable energy blocks [36].
- **System Integration and Market Roles:** To maintain grid stability, the Balancing Service Provider (BSP), often the aggregator, delivers technical reserves to the TSO or DSO, while the Balance Responsible Party (BRP) manages the financial liability of portfolio imbalances. This structure requires complex settlement rules and coordination to ensure that flexibility activations by aggregators are accurately accounted for across both local distribution and national frequency markets [37].

2.3.2 Wholesale market participation (Day-ahead and intraday energy markets)

Implicit demand response through wholesale price exposure represents the most accessible entry point for residential flexibility.

- **Market Mechanisms and Monetization:** DSF is optimized against price signals, such as SDAC (Day-Ahead) and SIDC (Intraday) couplings, to shift loads, manage EV/HVAC schedules, and enable arbitrage. For aggregators, this primarily serves to reduce procurement costs and mitigate portfolio imbalance risks, though the shift toward explicit demand response remains hindered by fragmented national regulations regarding baseline methodologies and aggregation rights [38], [39].
- **The Estonian Benchmark:** Estonia leads this transition with 100% smart meter coverage achieved by 2017 and a market where one-third of consumers are already on spot-price contracts. This advanced infrastructure provides a mature foundation for moving beyond simple price-based load shifting toward sophisticated, cross-border flexibility services as European market rules continue to harmonize under the Network Codes [40].

2.3.3 Frequency containment and balancing markets

Balancing energy is procured/activated close to real time when the system needs upward or downward regulation. The Electricity Balancing Guideline (EBGL) enables European platforms for exchanging balancing energy:

- **MARI** for manual FRR (mFRR) balancing energy exchange,
- **PICASSO** for automatic FRR (aFRR) balancing energy exchange,

For residential portfolios, the balancing energy layer is feasible when aggregation can provide reliable activation volumes and compliance data, but it is often bounded by minimum bid sizes, telemetry requirements, and the operational need to manage thousands of small devices within tight time limits.

- **FCR-N and frequency containment:** In the Nordic synchronous area, Frequency Containment Reserve for Normal operation (FCR-N) is a symmetric product activated automatically via local frequency measurement. The ENTSO-E describes the FCR Cooperation procurement as daily auctions with symmetric products, currently structured as four-hour products for the next delivery day. In the Finnish reserve context, Fingrid documents a minimum bid size of 0.1 MW for reserve bids [41]. Nordic technical requirements specify not only steady-state droop but also dynamic response properties. The amended methodology for additional FCR properties indicates that, for a ± 100 mHz step, FCR-N should reach roughly 63% response in 60 seconds and 95% in 3 minutes. These requirements align with the constraints addressed in the thesis framework, where symmetric reserve formation, endurance limits, and real-time tracking are treated jointly for residential portfolios [42].
- **mFRR and balancing energy:** Manual Frequency Restoration Reserve (mFRR) is manually activated and commonly associated with a formal full activation time of 15 minutes in Nordic practices, with process documentation aligning activation to 15-minute periods. At the European

level, ENTSO-E’s balancing implementation identifies the MARI initiative as the common platform for mFRR balancing energy exchange. For residential portfolios, mFRR remains challenging mainly due to minimum bid sizes (often MW-scale in many zones) and verification requirements [43].

- **Local voltage services:** Distribution-level flexibility procurement is motivated by the increasing difficulty of maintaining voltages within statutory bands under high DER penetration. European voltage-quality guidance is frequently aligned with EN 50160-type expectations; LV tolerance around 230 V $\pm 10\%$ and 400 V $\pm 10\%$ under steady-state conditions [44]. Policy and industry perspectives emphasise that flexibility procurement mechanisms in distribution networks should be designed to enable DSOs to contract flexibility efficiently while coordinating with TSO needs. However, the key research and deployment challenge is *coordination*: a DSO-driven activation that resolves a local voltage constraint can unintentionally create (or worsen) the BRP/TSO imbalance position unless the market framework defines (a) activation priority rules, (b) data exchange requirements, and (c) settlement logic that avoids double-counting or conflicting dispatch. This thesis’s model-free voltage regulation study positions DSF as an actionable alternative to excessive OLTC operations, demonstrating measurable reductions in tap changes while maintaining voltage compliance [paper IX].

2.3.4 Baltic/Estonian reserve markets

In the Baltic balancing capacity market design, the main frequency reserves are **FCR**, **aFRR**, and **mFRR** procured via daily auctions, and participation requires BSP prequalification and compliance with product definitions. In particular, current Baltic balancing capacity market rules define a **minimum bid quantity of 1 MW** (and 1 MW bid granularity) for FCR as well as for aFRR/mFRR capacity bids, an important barrier for residential portfolios unless the aggregation scale is large [45].

Fig. 2.4 shows the Baltic prequalification principles, specifying performance and data requirements that directly map to residential control/measurement challenges [46].

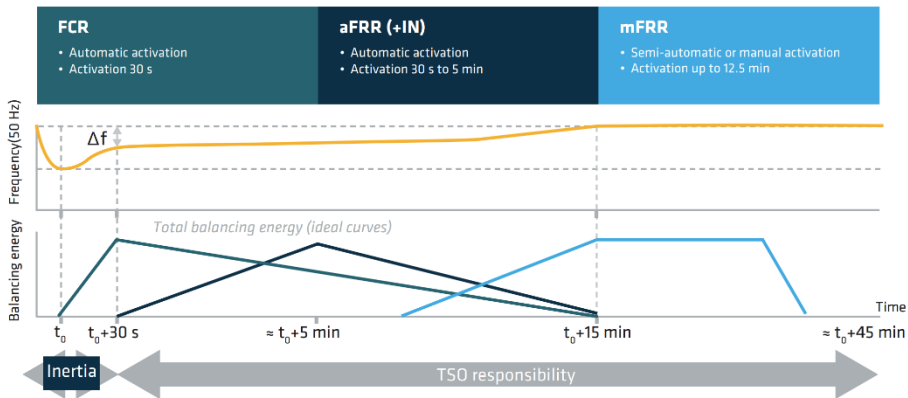


Figure 2.4. Balancing products and response times [46].

Since February 2025, the Baltic states, including Estonia, operate synchronously with the Continental European area, where frequency containment is procured as FCR under different technical and market terms. FCR requires activation to begin within 2 seconds of a frequency deviation and reach full activation within 30 seconds at a deviation of ± 200 mHz. aFRR, as defined in Baltic technical standards, has a full activation time of 5 minutes, reflecting its role in energy reservoir management and control hierarchy. mFRR allows a full activation time of up to 12.5 minutes, with a preparation period not exceeding 7 minutes. For verification purposes, balancing service providers must supply timestamped data for each technical entity within aggregated groups, with a temporal resolution of at least 10 seconds upon request [46].

The frameworks in this thesis are developed and validated against Nordic FCR-N specifications, and their results are not directly transferable to the Estonian, Baltic, or Continental European context without re-parameterization of activation dynamics, bid sizes, and revenue assumptions. FCR-N was selected as the benchmark because its symmetric, dynamically demanding profile represents a stringent test case; transferability is discussed further in Chapter 4.

2.4 Role of AI in demand-side flexibility operations

Traditional approaches to demand-side flexibility management commonly rely on static flexibility assumptions, predefined appliance operating windows, deterministic optimization, physics-based device models, or rule-based control logic. These methods can be effective for well-characterized industrial loads or for small portfolios with predictable operating patterns [47]. However, residential flexibility differs fundamentally because it is distributed across many small devices, strongly affected by occupant behavior, constrained by comfort preferences, and continuously influenced by weather, appliance availability, electricity prices, and local grid conditions. As a result, the available flexibility of a household or community is not a fixed technical parameter, but a time-varying and uncertain quantity that must be inferred from historical and real-time data [48]. When these inputs are derived from static assumptions rather than learned from data, the resulting schedules are prone to over-conservatism, comfort violations, and failure to anticipate rebound effects, undermining reliable market delivery. What is therefore needed is an integrated approach in which AI supplies the data-driven inputs, such as characterization, forecasting, and uncertainty modelling, that structured optimization methods then translate into market-compliant decisions [49].

AI methods are increasingly used in DSF because conventional rule-based, deterministic, and purely model-based approaches struggle to represent the non-linear, high-dimensional, behavior-dependent, and uncertain nature of residential flexibility. Rather than a single optimization task, DSF operates as an end-to-end pipeline, transforming heterogeneous household data into flexibility forecasts, risk assessments, and market-compliant control actions. AI supports the full flexibility timeline, including characterization, forecasting, and optimization, while increasingly addressing consumer-centric evaluation, privacy, and explainability to enhance trust and adoption [Paper I]. Machine learning applications in DSF can be grouped into four main paradigms, each with distinct operational roles, as shown in Table 2.1.

Table 2.1. Machine Learning Paradigms in Demand-Side Flexibility Operations

Learning Paradigm	Primary DSF Applications	Key Algorithms	Operational Advantages
Supervised Learning [50], [51], [52]	Flexibility forecasting, baseline estimation, load disaggregation	Linear Regression, Random Forest, SVM, XG-Boost, KNN	High interpretability; established validation methodologies; effective with structured historical data
Unsupervised Learning [53], [54], [55]	Consumer segmentation, pattern discovery, anomaly detection	K-means Clustering, PCA, G-means	No requirement for labeled training data; discovers hidden usage patterns; enables personalized flexibility services
Reinforcement Learning [56], [57], [58]	Real-time control, dynamic pricing response, sequential decision optimization	Q-Learning, Deep Q-Networks, Actor-Critic, PPO, SAC	Model-free adaptation to environment dynamics; optimal policy learning through interaction; handles high-dimensional state spaces
Deep Learning [59], [60], [61]	Complex pattern recognition, multi-horizon forecasting, end-to-end control	LSTM, GRU, CNN, Transformer, PINN	Superior performance with large datasets; automatic feature extraction; captures long-term temporal dependencies

2.4.1 From smart home to aggregator operations

A practical DSF architecture can be interpreted as a layered cyber-physical stack: (i) sensing and sub-metering, (ii) device modelling and flexibility characterization, (iii) forecasting and uncertainty modelling, (iv) optimization and dispatch, and (v) verification and consumer interaction. HEMS coordinates flexible devices (HVAC, water heater, appliances, PV, BESS) through smart plugs and a gateway, while an AI engine integrates exogenous signals (weather, price, DR signal) and behavioral features to output flexibility quantification and control decisions [62], [63].

Fig. 2.5 highlights an important operational distinction: DSF is simultaneously data-driven and market-facing. DSF must interface with energy and flexibility markets through the aggregator/TSO/DSO interaction, which motivates AI models that (i) forecast demand and flexibility, (ii) allocate device actions under constraints, and (iii) reduce penalty exposure by controlling under-delivery risk.

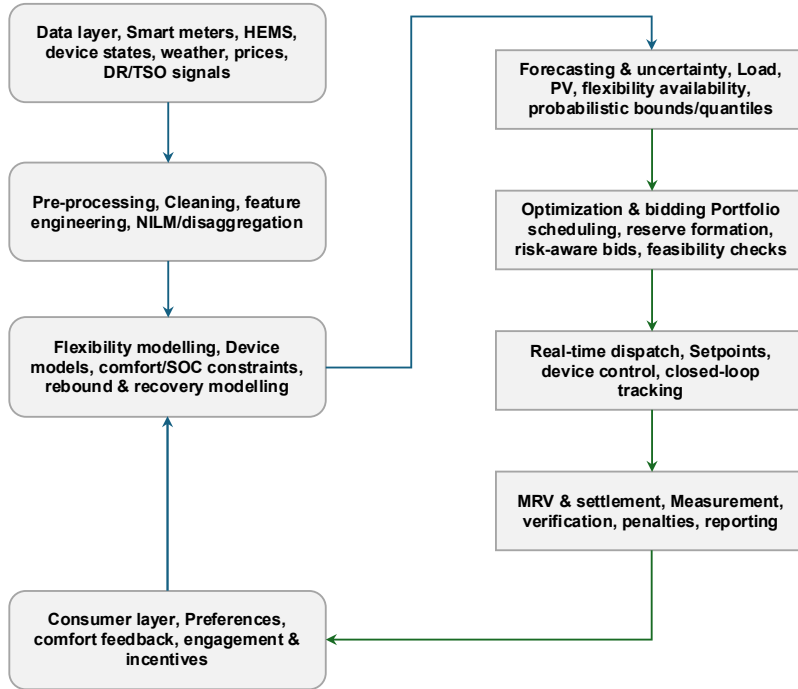


Figure 2.5. AI-enabled DSF operational pipeline for residential aggregation.

2.4.2 AI for flexibility optimization and control

In demand-side flexibility studies, the optimization objective depends on the operational context. For household energy management, the objective is often electricity-cost minimization or peak-demand reduction. For reserve provision, the objective is usually to maximize feasible reserve capacity while limiting under-delivery risk and user discomfort. Optimization is the layer where flexibility is converted into actions: appliance schedules, HVAC setpoints, EV charging/discharging, BESS dispatch, and coordinated control policies. Flexibility optimization in AI-enabled environments involves maximizing energy efficiency, reducing peak demand and energy costs, and improving user comfort through intelligent scheduling of flexible loads. The optimization problem definition must integrate user-controlled and system-controlled measures, with key objectives including minimizing energy consumption, maintaining thermal comfort, reducing operating costs, and minimizing thermal discomfort hours. AI enters optimization in the following main ways:

- **Learning-assisted scheduling and MPC:** Data-driven predictive control and ML-assisted MPC learn predictive building/device models and embed them in constrained optimization. The reviewed studies include cases reporting substantial reductions in cooling energy and comfort constraint violations using data-driven control approaches [64].
- **Deep reinforcement learning (DRL) control policies:** RL is attractive when explicit environment models are hard to maintain; the review highlights that RL methodologies for control tasks do not generally require an explicit

environment model, making them suitable for high-dimensional decision variables such as user preferences and appliance states [65].

- **Hybrid AI + optimization (metaheuristics, multi-objective optimization):** The review documents a strong trend toward hybrid approaches (e.g., ANN combined with evolutionary optimization, clustering + NSGA-II) for cost and discomfort reduction and for balancing multiple competing objectives [66].

Appliance Scheduling Optimization: AI techniques strategically operate flexible appliances to reduce electricity cost, shift consumption away from high-price or congested periods, and reduce peak demand. Load shifting adjusts appliance operation to off-peak times or temporarily disconnects certain loads based on scheduling algorithms that incorporate user preferences.

Load shifting techniques manage energy demand by adjusting appliance operation to off-peak times or disconnecting certain loads. Scheduling optimization includes adjusting HVAC temperatures, coordinating electric vehicle charging, and managing battery storage systems, which are vital for integrating distributed energy resources and optimizing grid services [67]. Reinforcement learning has become a key approach for scheduling under uncertainty. An inverse reinforcement learning model for appliance scheduling achieved a mean absolute error of 0.021 by learning user preferences from past consumption data without explicit input [68]. This approach reduces manual programming while maintaining comfort. An artificial neural network model lowered average electricity costs by 28.67% for electric vehicles and flexible appliances [69]. RL-based algorithms for dynamic pricing and consumption scheduling derived optimal schedules from observed retail prices, enhancing learning for both providers and customers [70]. A proximal policy optimization DRL agent for PV-battery storage systems effectively handled continuous action spaces and maximized net revenue through safe scheduling schemes [71].

Energy Optimization: Machine learning algorithms at the building and community level focus on providing energy conservation through improved insulation, efficient systems, renewable energy integration, and smart technology. Machine learning algorithms enhance these efforts by identifying energy-saving opportunities and managing battery storage systems using energy prices, consumption data, and grid conditions to optimally control charging/discharging, HVAC operations, and other flexible loads [72]. These algorithms must balance energy savings with user comfort, necessitating careful data-driven strategies that respect occupant preferences and behavioral patterns.

An adaptive ANN-based MPC system for predicting air temperatures in office and lecture settings, integrated with hybrid optimization, achieved maximum energy efficiency while ensuring indoor comfort [73]. This approach surpassed PID-based thermostat control, reducing cooling energy consumption by 58.5% in offices and 36.7% in lecture theatres. Additionally, a data predictive control method using random forests achieved a 24.9% reduction in cooling energy consumption and a 72.0% decrease in comfort constraint violations [74]. Machine learning-driven robust MPC for sustainable multi-zone buildings decreased electricity costs by 6.9% while enhancing thermal comfort and system stability amid weather forecast uncertainties [75]. Moreover, an LSTM-PSO approach yielded 9.41% energy savings [76], and a DRL-aided bi-level multi-period battery energy storage strategy improved planning efficiency for microgrid operations through a rainbow agent with quantile regression [77].

2.4.3 AI for flexibility characterization

Characterizing flexible load for demand-side flexibility involves evaluating the energy consumption of distributed energy resources, their response characteristics, and adaptability to grid fluctuations. Flexibility can be quantified across power, energy, and time dimensions, assessing the correlation between shiftable energy volume and cost, as well as the duration of sustainable power change. Additional relative metrics include flexibility as a percentage of on-site generation, self-consumption, storage efficiency, demand response potential, power variation, ramping rate, and overall system flexibility scoring systems. In practice, characterization commonly requires:

- **Disaggregation and appliance identification**, where AI-enabled NILM supports extracting flexible appliance states from aggregated measurements when high-resolution sub-metering is unavailable.
- **Clustering and profiling** (e.g., k-means) to build household groups and demand response
- **Supervised learning** (RF/XGBoost/SVM/linear models) to map features (weather, time-of-day, usage patterns) to flexibility indicators (e.g., peak shaving capacity, duration capability).

Flexibility characterization enables aggregators to optimize asset portfolios by quantifying responsive loads that adapt to energy price fluctuations. This process categorizes flexibility resources into quantitative, qualitative, and control domains, integrating these characteristics with ramping capacity, rebound effects, and aggregator activation signals for effective grid service utilization. The flexibility index measures a building's capacity to respond to grid demands, considering the interplay between aggregator penalty signals and demand adjustments [78].

AI is crucial in flexibility characterization, employing feature engineering and non-intrusive load monitoring algorithms to analyze the electricity consumption of flexible appliances in DR programs. Research indicates that AI techniques, such as random forest and k-means, surpass traditional methods in disaggregation and flexibility characterization. An XGBoost-based approach assessed residential energy flexibility through consumption pattern analysis, achieving up to a 25% reduction in peak-to-average consumption in DR models [79]. Heat pump flexibility is evaluated using energy and duration metrics, quantifying the time until energy consumption drops below baseline levels [80]. This framework assists aggregators in understanding the sustainable duration of flexibility activations, critical for market bidding. A dynamic two-stage optimization model enhances flexibility through submodular optimization, achieving up to 97% performance efficiency across scenarios [81].

Table 2.2 highlights the effectiveness of traditional machine learning models, particularly when integrated with other methods, in characterizing flexibility.

Table 2.2. Literature review of AI techniques for flexibility characterization in residential applications

Flexible Resource	Training Model	Methodology	Insights	Performance	Study
Shiftable appliances	Ada-Boost, KNN, Linear Regression,	Historic real-world data experiment	3D surface spanned by time, power levels, and maximum sustained duration using PDFs	Ada-Boost outperformed with MAE 21 and R^2 0.94	[82]
HVAC	ANN-multi-layer perceptron	Modelica for HVAC, EnergyPlus twin simulation	Framework for rapid DR potential assessment using indices with two common strategies	R^2 above 0.9 reveals DR program dynamics	[83]
HVAC	Soft Actor-Critic, Deep-RL	EnergyPlus archetype simulation	RL automates EMS, enabling flexibility from passive thermal mass under dynamic pricing	9.7% cost savings compared to baseline	[84]
Heat pump and thermal storage	MSP decision tree, Linear Regression	EnergyPlus co-simulation calibrated to ASHRAE	DR-based flexibility capabilities for residential buildings	39% and 37.9% reduction in utility generation and emissions	[85]
Shiftable appliances, EV	XGBoost	Data-driven simulation using real-world data	Flexibility quantified by power and start-time distribution based on non-fixed power values	Peak-to-average consumption reduced up to 25%	[86]
Individual heat pump	LSTM, GRU, RNN	Data-driven simulation using real-world data	Duration of forced on/off mode measured by comparing predicted flexibility with forecasts	GRU outperformed in flexibility prediction, followed closely by LSTM	[87]
Flexible appliance	Minibatch k-means	Data-driven simulation using REDD dataset	NILM extracts appliance states and usage patterns; calculates flexibility based on historical data	F-score of 0.9 compared to semi-supervised learning	[88]
Flexible load	FCNN, LSTM, Decision Tree, SVM	Data-driven simulation using real-world data	Digital platform for energy prediction and flexibility detection through prediction and classification	LSTM best for forecasting (MSE/MAE); SVM 91.3% classification accuracy	[89]

2.4.4 AI for flexibility forecasting

Flexibility forecasting aims to predict **adjustable energy quantities** (up/down) over operational horizons (minutes to day-ahead), which supports (i) market bids, (ii) device readiness, and (iii) penalty-risk management. AI improves flexibility forecasting by automating large-scale data analysis and predicting future energy demand patterns. Accurate day-ahead and hour-ahead predictions offer insight into energy-shifting flexibility and associated costs, enabling aggregators to optimize portfolio commitments across multiple markets. These forecasts are essential for anticipating customer response to flexibility activation signals and avoiding under-delivery penalties.

Key modelling patterns include:

- **Sequence models (LSTM/GRU, Bi-LSTM)** for nonlinear temporal dependencies in load/thermal dynamics and peak/valley forecasting.
- **Hybrid forecasting** (e.g., optimization-enhanced LSTM such as GA-triggered LSTM) to improve accuracy where feature selection and non-stationarity are challenging.
- **Transformer/attention-based models** (e.g., TFT) to capture long-range dependencies and identify significant temporal patterns, particularly when historical data is noisy or limited.

A significant finding for practical deployment is that a two-layer ANN can accurately forecast the demand flexibility of aggregated residential loads with just 5% smart meter coverage [90]. This result has important implications for scalability, suggesting that comprehensive submetering may not be necessary for effective flexibility forecasting at the portfolio level. Transfer learning combined with Temporal Fusion Transformer has been shown to improve load demand prediction in buildings with limited historical data [91], addressing the common challenge of data scarcity in emerging flexibility markets.

For battery state of charge estimation, a temporal-frequency dual attention mechanism network was developed to encode time-domain features and capture complex dependencies [92]. This approach enables more accurate forecasting of available storage flexibility, essential for participation in fast response markets.

Literature review in Table 2.3 indicates that deep learning models have consistently outperformed traditional machine learning models across various forecasting tasks and demand sectors. LSTM models demonstrate superior performance in both thermal load and electricity consumption forecasts, highlighting their capability to handle non-linear patterns and long-term dependencies in time-series data. Machine learning models enhanced with optimization algorithms (e.g., GA-enhanced LSTM) also show strong performance, particularly in residential and commercial electric load forecasting. SVM, when combined with clustering techniques like k-means, provides competitive accuracy in commercial settings.

Table 2.3. Literature review of AI techniques for flexibility forecasting across demand sectors

Objective	Demand Sector	Data Inputs	AI Model	Forecasting Performance	Study
Electric Load	Residential	Weather, Occupancy	GA-Enhanced LSTM	RMSE 0.61% short-term, 0.56% medium-term	[93]
Electric Load	Commercial	Weather	SVM, FFNN	SVM better with MAPE 1.90%, RMSE 3.3%	[94]
Electric Demand	Commercial, Residential	Weather	LSTM	Superior performance across heating, cooling, intermediate seasons	[95]
Thermal Load	Commercial	Weather	NARX RNN, ϵ -SVM-R	NARX RNN outperformed ϵ -SVM-R in MAE and MSE	[96]
Peak Load	Residential	Weather, Occupancy	Deep Bi-LSTM S2S	Outperformed LMBP-ANN and shallow LSTM on holidays and normal days	[97]
Indoor Temperature	Residential	Weather	LSTM, GRU	GRU 9% lower RMSE than LSTM; 32% lower than LR	[87]
Appliance Consumption	Residential Household	Historical consumption	CLARA, SVM, ANN	SVM 99.6% accuracy	[98]
HVAC Load	Residential	Weather	XGBoost, Linear, Lasso, RF, Decision Tree	XGBoost most accurate forecast	[99]
Electricity Consumption	Campus Building	Weather, Occupancy	ANN, Linear Regression	ANN more stable for working day predictions	[100]
Power Consumption	Residential Household	Historical data	CNN, SVM, ANN	CNN outperformed with 0.59% MAE, 0.79% RMSE	[101]
Home Appliances	Residential Household	Consumption data	PCA, DNN, SVM	DNN outperformed SVM in all forecasts	[102]
Wind Speed	Distribution	Meteorological data	GNN, Transformer ^{LogSparse}	Outperformed LSTM and MLP	[103]

2.4.5 Challenges and Operational Limitations

While the potential of machine learning techniques to enhance demand-side flexibility exists, several limitations remain relative to traditional physical models.

- **Data availability and dataset quality:** The main barrier for AI-based residential flexibility is the lack of high-resolution, labeled, and behaviorally representative datasets. This limits model training, validation, and generalization to new households or portfolios. Also, ownership of the data and regulations around data sharing limits access to long-term labeled data.
- **Data Dependency and Non-Stationarity:** ML models typically assume stationary data distributions, an assumption frequently violated in dynamic energy systems where consumer behavior, weather patterns, and grid conditions evolve due to economic, technological, and policy changes. This results in decreased model accuracy over time as models struggle to adapt to non-stationary conditions.
- **Computational Demands:** Deep learning models require substantial computational resources, making real-time integration into energy management systems challenging. The need for continuous model updates to maintain accuracy in dynamic, decentralized environments introduces scalability challenges.
- **Exploration-Exploitation Trade-off:** In reinforcement learning for flexible load optimization, overemphasis on exploration leads to higher initial costs and inefficiencies, while excessive exploitation results in suboptimal long-term performance.
- **Physical Model Limitations:** While physics-based thermal modeling can effectively analyze rebound effects following flexibility provision, ML models often lack sufficient data reflecting these complex dynamics, necessitating hybrid approaches.

The above analysis has examined AI applications across flexibility characterization, optimization, and forecasting domains. To provide a consolidated perspective, Table 2.4 presents a systematic mapping between the core operational functions that residential aggregators must perform, and the AI methods best suited to each function.

Table 2.4. Mapping DSF operational functions to AI methods

DSF operational function (aggregator)	Typical AI task	Representative AI families highlighted in the review	Outputs used operationally	Key deployment caveat
Appliance/state observability (limited sensing)	NILM / state inference	Supervised ML, ensemble methods	Appliance states, usage patterns, flexible vs inflexible load segmentation	Errors propagate downstream (misestimated flexibility → wrong bids)
Flexibility characterisation	Feasible-set learning; DR profile extraction	XGBoost/RF/SVM + clustering; data-driven models	Power/time/energy flexibility indices; ramp & rebound-aware profiles	Requires frequent updating to handle behavioral drift
Flexibility forecasting	Short/medium-horizon prediction + uncertainty	LSTM/GRU, CNN hybrids, transformers (TFT), probabilistic methods	Quantile flexibility bounds; readiness probability; expected rebound	Nonstationarity degrades performance without adaptation
Optimization & bidding	Risk-aware scheduling; reserve formation	ML-assisted MPC; hybrid optimization; RL/DRL	Market-compliant bids; activation-feasible schedules	Computational burden vs real-time constraints
Real-time dispatch	Closed-loop tracking and policy control	DRL, adaptive control, ML-based setpoint control	Control setpoints; corrective dispatch; penalty mitigation actions	Safety/comfort constraints must be enforced explicitly
Consumer-centric operation	Preference learning; comfort modelling	IRL, behavior modelling, personalized forecasting	Comfort setpoints, flexibility budgets, opt-out likelihood	Trust/transparency becomes central (needs XAI)
Governance & compliance	Explainability, privacy, auditability	Federated learning; XAI (e.g., LIME/DeepLIFT)	Explainable decisions; privacy-preserving model updates	Regulatory/ethics expectations require audit trails

2.5 Summary

The state-of-the-art review highlights the growing importance of energy flexibility in modern power systems, particularly in the context of increasing renewable energy penetration, declining system inertia, and the evolving need for decentralized grid support. This chapter explored residential demand-side flexibility as a promising resource for supporting both balancing services and local network operation. It showed that residential flexibility is technically relevant because it can contribute to frequency support, balancing actions, and voltage management, while also creating value for aggregators and system operators through improved market participation and operational efficiency.

The review further showed that residential flexibility is inherently heterogeneous, since it arises from diverse household resources such as HVAC systems, water heaters, electric vehicles, battery storage systems, and shiftable appliances, each with different operational limits, response speeds, and comfort dependencies. For this reason, effective utilization of flexibility cannot rely on static assumptions alone, but requires proper characterization of its temporal, behavioral, and technical dimensions. The chapter also emphasized that flexibility must be understood not only as a physical capability, but as a market-facing and control-oriented resource that must satisfy product requirements, user comfort, and reliable delivery conditions.

In addition, the chapter reviewed the growing role of artificial intelligence in enabling flexibility quantification, forecasting, optimization, and control. The literature synthesis revealed that, although substantial progress has been made in these individual areas, existing studies often address them separately, leaving a weak connection between flexibility characterization, forecasting, bidding, and real-time coordination. This fragmentation limits the practical deployment of residential flexibility in real systems and market environments and establishes the need for an integrated methodological framework.

Therefore, this chapter provides the conceptual and methodological foundation for the next stages of the thesis. Building on the identified gaps, Chapter 3 develops a data-driven framework for quantifying demand-side flexibility from heterogeneous household appliances under dynamic user comfort conditions. Chapter 4 then extends this quantified flexibility into a forecast-driven aggregation and real-time coordination framework for balancing market participation, whereas Chapter 5 shifts the focus to the use of aggregated flexibility for model-free real-time voltage regulation in active distribution networks.

3 Quantification and Aggregation of Demand-side Flexibility

3.1 Overview of the proposed framework

The integration of renewable energy sources into modern power systems is crucial for achieving carbon neutrality, yet it poses significant operational challenges due to the intermittency and uncertainty of weather-dependent generation. These factors lead to frequent power imbalances and frequency deviations that jeopardize grid stability. To maintain frequency within acceptable limits, transmission system operators (TSOs) increasingly rely on ancillary services like Frequency Containment Reserves (FCR). Traditionally supplied by large-scale dispatchable generators, there are now opportunities for demand-side flexibility to enhance balancing services due to the rise of smart metering and distributed energy resources.

Residential flexibility encompasses controllable assets such as shiftable appliances (e.g., washing machines, dishwashers), thermostatically controlled appliances (e.g., heat pumps, HVAC systems), and battery energy storage systems (BESS). Shiftable loads enable up-regulation services by delaying operation, while TCAs and BESS can provide both up- and down-regulation, aligning with symmetrical regulation requirements set by TSOs like Fingrid for FCR-N provision. The effective use of these resources relies on advanced HEMS to schedule operations, alongside aggregators optimizing flexibility from multiple households to meet market participation criteria.

This chapter presents a comprehensive data-driven framework for quantifying and aggregating demand-side flexibility from heterogeneous residential appliances, specifically designed to enable symmetrical bidding in energy balancing markets. The methodology addresses critical research gaps identified in Chapter 2, particularly the need for dynamic flexibility quantification that accounts for evolving user behavior, the heterogeneity of appliance characteristics, and the stringent requirements of balancing market products. The proposed framework operates through two interconnected stages: first, machine learning-based flexibility quantification at the appliance level, considering dynamic user comfort zones; and second, hierarchical aggregation and sequential optimization to ensure market compliance while minimizing user discomfort. Figure 3.1 presents the overall workflow of the proposed framework.

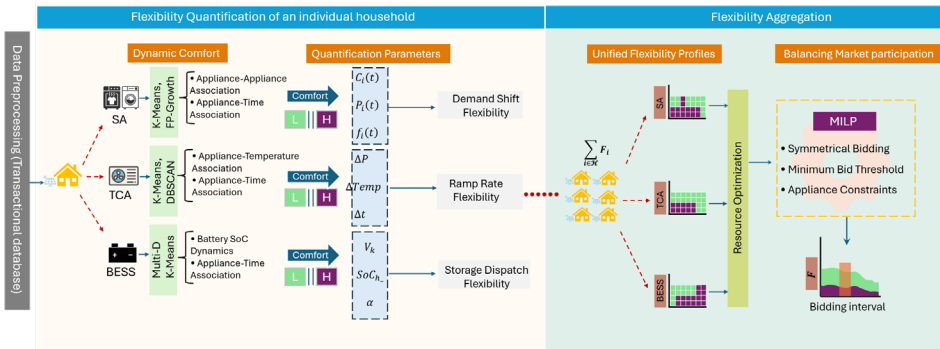


Figure 3.6. Proposed flexibility quantification and aggregation framework [paper III].

The key contributions of this chapter are fourfold:

- First, a **demand-shift flexibility** model is developed that characterizes shiftable appliance flexibility by incorporating controllability metrics, temporal dependencies, and appliance interactions. This model employs K-means clustering and FP-Growth association rule mining to define dynamic comfort zones that evolve with user behavior patterns.
- Second, a **ramp-rate flexibility** model quantifies the flexibility potential of thermostatically controlled appliances by identifying energy consumption patterns under varying weather conditions. This model integrates K-means clustering with DBSCAN density-based clustering to create a temperature-energy landscape that reveals flexibility opportunities across different operating conditions.
- Third, a **storage-dispatch flexibility** model assesses BESS flexibility by analyzing state-of-charge (SoC) variability using multidimensional K-means clustering. This model incorporates photovoltaic (PV) generation contributions to optimize battery dispatch under both high and low utilization scenarios.
- Fourth, a **hierarchical device-level aggregation** methodology creates unified flexibility profiles using a sequential mixed-integer linear programming (MILP) model. This optimization framework prioritizes low-comfort-disturbance flexibility while ensuring symmetrical bidding capabilities and compliance with minimum capacity thresholds for FCR market participation.

3.2 Flexibility Quantification

The proposed flexibility quantification framework employs appliance usage data and weather-related information to infer flexibility potential based on how these variables influence user behavior. Rather than assuming fixed operational margins, the models learn usage patterns and behavioral boundaries directly from historical data, ensuring that quantified flexibility reflects actual consumption dynamics and comfort preferences.

3.2.1 Demand-shift flexibility of shiftable appliances

This phase involves characterizing the flexibility of shiftable appliances (SA). Demand-shift flexibility refers to adjusting or shifting the energy consumption patterns of these appliances in response to external aggregator signals. This involves mining behavioral energy consumption patterns to ascertain associations between different appliances and their usage over time. The resulting information is used to determine the controllability of each appliance, a critical factor in assessing the flexibility of shiftable appliances, as it indicates the extent to which an appliance's operation can be adjusted to accommodate user preferences. The quantitative measure of controllability forms the basis for assessing the potential of demand-shift flexibility.

The flexibility characterization of SA depends on two key aspects: appliance-time association and appliance-appliance association. The first one assists in identifying the appliance's feasible operating period by analyzing user behavior, while the latter examines how the operation of one appliance depends on the operation of another.

In the proposed methodology, the temporal comfort zones of the user are defined by analyzing appliance operating periods. Consumer historical consumption data is examined to consider seasonal variations and to establish a baseline comfort zone. These comfort zones are not static; rather, they are updated weekly based on a rolling one-year

window. This dynamic update process ensures that the model remains responsive to any new trends or changes in user behavior. These dynamic comfort zones indicate feasible operating periods in a day during which an appliance can offer flexibility upon request by an aggregator, reflecting a flexibility-on-demand approach.

To identify these comfort zones and the associated potential flexibility, K-means is applied to identify the potential state candidates using energy consumption data $x = x_1, x_2, \dots, x_T$, where T denotes the total number of data samples in the considered window. The energy consumption data is first converted into a binary format, and weekly data is extracted to capture user behavior across different weeks. K-means clustering is applied for weeks with sufficient variance to categorize the data into three distinct clusters. Cluster 0 represents periods of inactivity for the appliance during the day. Cluster 1 corresponds to a lower comfort disturbance zone, characterized by moderate usage periods, where the appliance offers higher flexibility since users are more willing to adjust their usage. Cluster 2 denotes a high comfort disturbance zone with frequent usage, reflecting a more regular pattern where users are less inclined to modify their usage, resulting in lower flexibility availability.

These clusters reflect the dynamic nature of user behavior and appliance usage patterns in a residential setting. The variable $Comfort(K, w)$ is introduced to express the comfort zones of a user in terms of appliance usage at different times for flexibility analysis. These zones are updated weekly to reflect recent changes in user behavior.

$$Comfort(K, w) = \begin{cases} \text{Higher Zone} & | \Delta H_i(t) \in C_{high}^w \\ \text{Lower Zone} & | \Delta H_i(t) \in C_{low}^w \end{cases} \quad (3.1)$$

For high comfort zone:

$$C_{high}^w = C_{high,initial} \cup C_{high,updated} \quad (3.2)$$

For low comfort zone:

$$C_{low}^w = C_{low,initial} \cup C_{low,updated} \quad (3.3)$$

where $\Delta H_i(t)$ represents the time difference in the association of the appliance i with comfort zones K over time t . $C_{high,initial}$ and $C_{low,initial}$ denotes the initial high and low comfort zones based on historical data, while $C_{high,updated}$ and $C_{low,updated}$ represent the weekly updated comfort zones that reflect recent changes in user behavior. C_{high}^w and C_{low}^w are the high and low comfort zones for the current week w , respectively.

The appliance-appliance association analyzes frequent itemsets and association rules to determine how appliances interact with each other. The association strength γ between different appliances is derived from frequent itemset mining using the FP-Growth algorithm, reflecting the conditional probability that one appliance is active, given that another is also active. The strength of these associations is assessed using measures like support and the Kulczynski measure (Kulc). This requires transactional data generation, which is a continuous process, invalidating old frequent patterns and building new ones. Therefore, an incremental and progressive strategy is imperative, where these updates are considered, and the discovered frequent patterns are duly maintained. Let D represent a daily energy consumption transaction database with a series of transactions, $\Gamma = I_1, I_2, \dots, I_k$, where each transaction contains k appliances,

and each I_i (where $1 \leq i \leq k$) represents a distinct appliance within that transaction. A matrix representation is derived from time segments, where rows represent transactions of an itemset and columns represent the operational or non-operational state of each appliance. A simplified transactional matrix looks as follows:

$$D = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \quad (3.4)$$

The support of an itemset X represents the frequency with which a particular combination of appliances appears in the transactional database D . Mathematically, it is defined as:

$$\text{support}(X) = \frac{\text{Number of transactions containing } X}{\text{Total number of transactions in } D} \quad (3.5)$$

The higher the support, the more frequently that particular itemset appears in the transactional database, indicating a stronger and more consistent association between the appliances. For the extraction of these frequent itemsets, the FP-Growth algorithm is used, which discerns frequent patterns without exhaustive candidate generation in a computationally efficient manner. To assess the strength and directionality of these associations, the Kulczynski ($Kulc$) measure is utilized:

$$Kulc(A, B) = \frac{1}{2} \left(\frac{\text{support}(A \cap B)}{\text{support}(A)} + \frac{\text{support}(A \cap B)}{\text{support}(B)} \right) \quad (3.6)$$

This measure provides an average conditional probability of appliance A being active, given that the appliance B is also active. Both the appliance-time (ΔH_{ki}) and γ are then utilized to determine the controllability of shiftable appliances. The controllability, $C_i(t)$, of an appliance i is given as:

$$C_i(t) = \Delta H_{ki}(t) + \sum_{j=1}^n \gamma_j \Delta H_{kj}(t) \quad (3.7)$$

where $\Delta H_{kj}(t)$ represents the time difference in the appliance-time association of appliances j . Now, the maximum available flexibility of an appliance i is quantified as:

$$F_i(t) = C_i(t) * \frac{P_i(t)}{f_i(t)} \quad (3.8)$$

where $f_i(t)$ is the average operating usage rate of shiftable appliances that represents the number of daily usage cycles of appliances across various comfort zones and $P_i(t)$ is the active power of each appliance. Total aggregated demand-shift flexibility is the sum of the individual flexibility of each shiftable appliance.

3.2.2 Ramp-rate Flexibility

Ramp rate flexibility refers to the ability of thermostatically controlled appliances (TCA), such as heat pumps, and HVAC systems, to ramp up or ramp down their energy

consumption based on varying external conditions. These appliances introduce challenges in energy management systems due to the intricate balance between user comfort, weather conditions, occupancy, and inherent operational characteristics of appliances. The proposed method integrates appliance-time and appliance-temperature associations by utilizing both K-means clustering and DBSCAN algorithms.

K-means clustering is applied to the consumption data of TCAs to identify the higher and lower comfort disturbance zones using appliance-time association. User comfort in this case represents a time-of-day period where the user historically relies on TCAs to maintain their preferred indoor temperature, so changing its operation there would create more discomfort than in other periods. Outdoor temperature is considered as a decision factor in determining how much flexibility could be provided based on temperature change. It will help both the consumer and aggregator in understanding the possible flexibility potential by considering the weather forecast.

Following this, DBSCAN is applied to each K-means cluster to assess variations in energy consumption with respect to external temperature. This approach creates a temperature-energy landscape for each cluster, indicating the potential energy change within the temperature range of that cluster.

DBSCAN clusters represent two distinct TCL operational states that depend on external temperatures. The high-density cluster represents normal operating conditions with low appliance power consumption variability due to moderate temperature changes, while the low-density cluster represents less frequent conditions with significant temperature and consumption variations, suggesting seasonal influences or unconventional usage patterns from the user.

These appliance-time and appliance-temperature associations provide ramp-rate flexibility to balance energy use and consumer comfort. Two key metrics are calculated for each DBSCAN cluster within the indicated outdoor temperature range based on the market time interval: the peak power consumption, denoted as P_{max} , and the standard deviation of the power consumption, represented by σ . The difference, ΔP represents the amount of energy that can be provided for flexibility operations when the temperature lies in the specific range determined by the DBSCAN clustering.

$$\Delta P = P_{max} - |\sigma| \quad (3.9)$$

The ramp-rate flexibility, F_r , quantifies the rate of change in energy consumption under varying temperature conditions and is defined as:

$$F_r = \frac{\Delta P}{\Delta Temp \times \Delta t} \quad (3.10)$$

where $\Delta Temp$ represents the change in outdoor temperature between the same two consecutive data points and Δt is the number of hourly timestamp market intervals for which the customer is available to provide flexibility to the aggregator.

3.2.3 Storage-dispatch Flexibility

Battery energy storage systems significantly enhance the energy flexibility of a residential unit by efficiently storing and dispatching energy. Storage dispatch flexibility focuses on how much room is available to modify the battery state of charge while remaining within

the observed operating range. The principal objective is to ascertain the available capacity within the battery SoC for flexibility operations. Several factors contribute to the characterization of storage dispatch flexibility, such as the load supplied by the grid, photovoltaic (PV) and battery storage capacity, battery SoC, solar irradiance, charging/discharging rate, and outside temperature. From a practical point of view, BESS owners are usually reluctant to share their SoC with markets and grid operators for extended periods (beyond a few hours). Therefore, maintaining a balance between household energy demand and BESS flexibility operations is crucial. A high SoC indicates more potential for flexibility services, while a low SoC limits flexibility.

This approach quantifies BESS flexibility using a dynamic time-series tracking analysis of battery SoC, categorizing battery operation into high and low utilization clusters. By developing metrics around this, battery flexibility is measured based on its variability and adaptability during these periods. A multidimensional K-means clustering is used to group battery SoC into high and low-utilization cluster periods by capturing complex interactions between different influencing factors, contributing to the characterization of storage dispatch flexibility. These utilization periods are updated daily based on weather forecasts to account for variations in user behavior towards BESS usage.

Examining the SoC trends within distinct clusters assists in identifying battery charging and discharging patterns. If these clusters show a rising trend or exceed a set limit, the battery provides SoC reserve in that period. However, decreasing SoC limits flexibility since the battery discharges for local needs, possibly affecting user needs and battery health. Key to this concept is understanding the charging and discharging patterns, which are influenced by user behavior and energy demands. SoC variability quantifies the extent of fluctuations in battery charge levels during high and low utilization periods in each cluster. A higher variability in SoC indicates a more responsive and flexible BESS that assists in optimizing energy usage and potentially contributing to grid stability.

For each K-means cluster, battery variability, V_k , is calculated as:

$$V_k = \frac{(SoC_{c,max} - SoC_{c,min})}{\Delta T} \quad (3.11)$$

where $SoC_{c,max}$ and $SoC_{c,min}$ represent the maximum and minimum SoC in each cluster, respectively, and ΔT is the normalization factor, representing the number of hourly timestamps in the respective cluster k .

In order to gain a comprehensive understanding of battery charging and discharging cycles on an hourly basis, the battery adaptability rate, α , is also determined as:

$$\alpha = \frac{(SoC_{h,max} - SoC_{h,min})}{\Delta t_r} \quad (3.12)$$

where $SoC_{h,max}$ and $SoC_{h,min}$ represent the maximum and minimum SoC during each market hour within each cluster and Δt_r accounts for the number of market timestamps. A high α score means that the battery can adapt to changes in load demand and vary its SoC in response, indicating a more dynamic battery usage.

A flexibility reserve metric, F_{res} , is formulated in terms of battery variability and rate of adaptability. The F_{res} value estimates the battery capacity to supply energy for grid flexibility services, thus offering a comprehensive insight into the overall flexibility of the battery during each operating period. The flexibility of BESS for each cluster k is calculated as:

$$F_{res,k} = \frac{V_k * \alpha(SoC_{h_norm})}{\Delta t_r} \quad (3.13)$$

where SoC_{h_norm} represents the normalized SoC values. This storage dispatch flexibility is multiplied by battery capacity to determine how many kWh the battery can provide. However, F_{res} should not exceed a certain maximum limit for the effectiveness of this metric. This limitation is necessary to ensure that when the battery SoC is rising, there is increased potential for flexibility. Conversely, less flexibility is available during discharge because the battery already caters to the load. By using the initial SoC, (14) provides a baseline to assess the starting BESS capacity for flexibility operations.

$$F_{init} = SoC_{initial} - SoC_{h_min} \quad (3.14)$$

The overall unified flexibility is the sum of the individual flexibilities of shiftable appliances, TCAs, and BESS in a comfort zone K at time t :

$$F_{unified} = \sum_{i=1}^n F_{i,K}(t) \quad (3.15)$$

3.3 Flexibility Aggregation

The aggregation methodology developed in this chapter is designed specifically to construct symmetric reserve capacity compliant with FCR-N requirements in the Nordic balancing market, specifically a minimum bid of 0.1 MW (Fingrid), a 15-minute product window, and symmetric up/down capacity. Flexibility aggregation within a residential community employs a hierarchical and device-level approach to dynamically assess and leverage the capabilities of individual home appliances in adjusting their energy consumption. The hierarchical aggregation combines the flexibility of all appliances across the residential community, creating unified community-level flexibility profiles optimized using a sequential MILP model for symmetrical participation in the flexibility reserve market. The primary objective of the model is to maximize the utilization of available flexibility across different households and appliance types, with prioritization of lower comfort disturbance zone flexibility over higher comfort zone flexibility while adhering to operational constraints such as symmetrical bidding and minimum bid requirements. Symmetrical bidding requires that the aggregated flexibility bid equally support both upward and downward flexibility regulation, maintaining a balanced offering that can adapt to fluctuating energy demands. Shiftable appliances only contribute to upward regulation by delaying their operation, while TCAs and BESS contribute to both upward and downward regulation based on current appliance headroom. Fig. 3.2 shows the workflow of the proposed flexibility quantification and aggregation method.

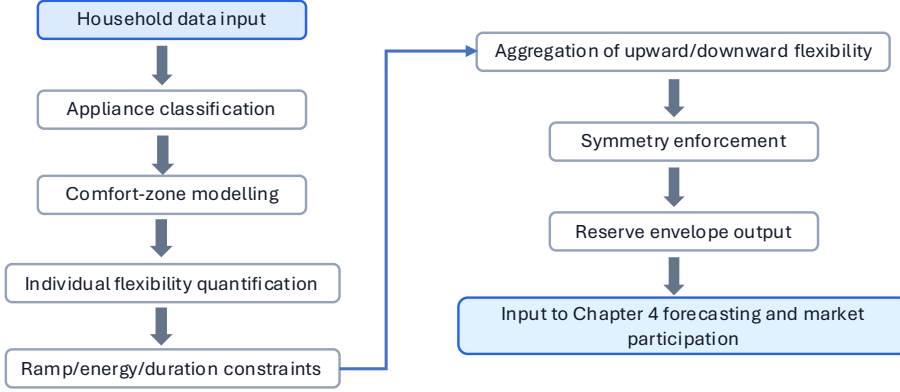


Figure 3.7. Workflow of the proposed flexibility quantification and aggregation method, showing how appliance-level flexibility is transformed into an aggregate symmetric reserve envelope.

The model considers a set of households $\mathcal{H}$, indexed by i , a temporal framework divided into discrete hours $\mathcal{T}$, indexed by t , and the set of appliance types as $\mathcal{A}$, indexed by a . The flexibility available from appliance a in household i during hour t for the lower and higher comfort zones is denoted as $P_{i,a,t}^{\text{low}}$ and $P_{i,a,t}^{\text{high}}$, respectively. To ensure that $P_{i,a,t}^{\text{low}}$ is prioritized over $P_{i,a,t}^{\text{high}}$, a sequential optimization approach is employed, where the first stage maximizes the utilization of $P_{i,a,t}^{\text{low}}$ and the second stage optimizes $P_{i,a,t}^{\text{high}}$ after fully utilizing the lower comfort zone. $U_{i,a,t}^{\text{up}}$ and $U_{i,a,t}^{\text{down}}$ are the binary decision variables indicating whether a given appliance in a specific household provides up-regulation or down-regulation at a particular time based on available headroom. The total up-regulation and down-regulation flexibility at time t are represented by $P^{\text{up}}(t)$ and $P^{\text{down}}(t)$, respectively. The objective function of the model aims to maximize the sum of all utilized flexibility, with a preference for utilizing flexibility from the lower comfort zone. This is formulated as:

$$\max \sum_{i \in \mathcal{H}} \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} (U_{i,a,t}^{\text{up}} + U_{i,a,t}^{\text{down}}) (P_{i,a,t}^{\text{low}} + P_{i,a,t}^{\text{high}}) \quad (3.16)$$

$$\text{Subject to } P^{\text{up}}(t) = P^{\text{down}}(t), \forall t \in \mathcal{T} \quad (3.16a)$$

$$P^{\text{up}}(t) \geq P_{\min}(1 + \beta), \forall t \in \mathcal{T} \quad (3.16b)$$

$$P^{\text{down}}(t) \geq P_{\min}(1 + \beta), \forall t \in \mathcal{T} \quad (3.16c)$$

$$U_{i,a,t}^{\text{up}} + U_{i,a,t}^{\text{down}} \leq 1, \forall i \in \mathcal{H}, a \in \mathcal{A}_{HVAC}, t \in \mathcal{T} \quad (3.16d)$$

$$U_{i,a,t}^{\text{up}} + U_{i,a,t+1}^{\text{up}} \leq 1, \forall i \in \mathcal{H}, a \in \mathcal{A}_{TCA}, t+1 \in \mathcal{T} \quad (3.16e)$$

$$U_{i,a,t}^{\text{down}} + U_{i,a,t+1}^{\text{down}} \leq 1, \forall i \in \mathcal{H}, a \in \mathcal{A}_{TCA}, t+1 \in \mathcal{T} \quad (3.16f)$$

$$U_{i,a,t}^{\text{up}} = 0, \text{ if } \text{SoC} \leq 45, \forall i \in \mathcal{H}, a \in \mathcal{A}_{BESS}, t \in \mathcal{T} \quad (3.16g)$$

where, β represents bid safety margin. The up-regulation and down-regulation capacities at any time t are determined by the aggregated flexibility provided by all appliances in all households, given by:

$$P^{\text{up}}(t) = \sum_{i \in \mathcal{H}} \sum_{a \in \mathcal{A}} (U_{i,a,t}^{\text{up}} (P_{i,a,t}^{\text{low}} + P_{i,a,t}^{\text{high}})) \quad (3.17)$$

$$P^{\text{down}}(t) = \sum_{i \in \mathcal{H}} \sum_{a \in \mathcal{A}} (U_{i,a,t}^{\text{down}} (P_{i,a,t}^{\text{low}} + P_{i,a,t}^{\text{high}})) \quad (3.18)$$

Expression 3.16a introduces the requirement for symmetrical bids, ensuring that the amount of energy available for up-regulation matches that for down-regulation for each timestamp. Constraints (3.16b) and (3.16c) establish a minimum bid threshold to avoid penalties. Expression (3.16d) prevents simultaneous up/down regulation; (3.16e) and (3.16f) prevent consecutive activations. Constraint (3.16g) ensures safe BESS operation by preventing excessive discharge.

3.4 Case Study

The proposed methodology is evaluated through two case studies designed around participation in Fingrid's FCR-N market, which requires symmetrical bidding and a minimum bid size of 0.1 MW. The first case study focuses on the flexibility potential of an individual household, while the second evaluates the aggregation of quantified flexibility across a larger residential community.

In the first case study, shiftable and thermostatically controlled appliance data are taken from the AMPds dataset, whereas solar PV and battery storage information are taken from the Cornwall LEM dataset. One year of high-resolution data is aggregated into 30-minute intervals to build a behavioral transactional database. In the second case study, flexibility is aggregated across 150 households using Pecan Street data. Missing values are imputed, outliers are removed, and the data are standardized before synchronization to 1-hour resolution.

For ML stages, K-means is configured with $n_{\text{init}} = 5$ and $\text{max_iter} = 300$, and the number of clusters is selected by silhouette analysis. FP-Growth uses a minimum support of 0.1 and a confidence threshold of 0.8. DBSCAN is configured with $\text{eps} = 0.7$ and $\text{min_samples} = 5$. The sequential MILP problem is solved with Gurobi using a 0.1% optimality gap on a workstation with an Intel Core i7 processor and 64 GB RAM.

3.4.1 Case Study 1: Flexibility Potential of an Individual Household

The flexibility potential of an individual household is determined on a day-ahead basis, utilizing one year of historical data for model training. Subsequently, the data from the most recent day is employed to conduct the quantification assessment, reflecting recent usage behavior.

This case study characterizes the available flexibility of three shiftable appliances: washing machine, clothes dryer, and dishwasher, with power ratings of 1350 W, 4700 W, and 1270 W, respectively. Dishwasher data is used for detailed analysis. The process starts with mapping out appliance-time associations. K-means clustering identifies lower and higher comfort zones for each appliance, as shown in Fig. 3.3. The dynamic behavior of a customer regarding dishwasher usage over the weeks is shown in Fig. 3.4.

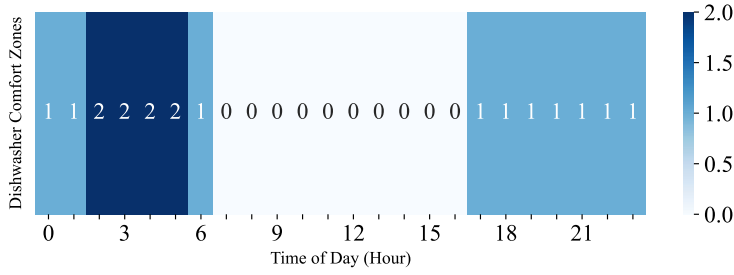


Figure 3.8. Appliance to time association of shiftable appliances.

Appliance-appliance association is evaluated by applying the FP-Growth algorithm to identify frequent appliance usage patterns. Conditional probabilities and the Kulc measure are used to quantify appliance associations, while appliance controllability is incorporated to compute flexibility, as shown in Table 3.1.

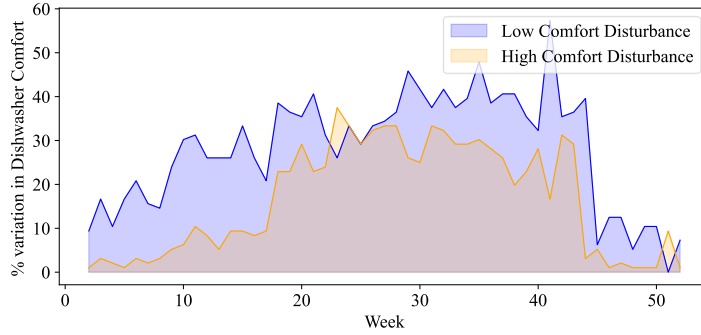


Figure 3.9. Dynamic variation of dishwasher comfort zones across weeks.

Table 3.5. Statistical Measures Illustrating Appliance Usage Associations

Comfort	Appliance Association		Kulc	$C_i(t)$	ΔH_{ki}	$F_i(t)$
High	Dishwasher	- Cloth Dryer	0.3	3.87	3.5	0.620
		- Washing Machine	0.3			
Low	Dishwasher	- Cloth Dryer	0.8	16.48	8	1.680
		- Washing Machine	0.2			

Fig. 3.5 highlights user comfort zones regarding heat pump usage. The influence of external temperature on heat pump power consumption (3.3 kW) is assessed by applying DBSCAN, as illustrated in Fig. 3.6. Following this, the maximum power, P_{max} and standard deviation, σ , for each DBSCAN cluster under normal operating conditions, are computed for ΔP . Table 3.2 summarizes the ramp-rate flexibility of the heat pump under seasonal scenarios.

From the flexibility analysis of the heat pump, it is observed that F_r has a strong relation with user comfort in the sense that with the increase in flexibility duration or with a greater change in outside temperature, F_r tends to decrease to keep the comfort level of the user intact. For instance, in high comfort zones, lower appliance controllability leads to lower flexibility values, compared to low comfort zones, which have greater appliance controllability. Moving from the warmer band (10–14 °C) to the

colder band (3–7 °C) increases σ and reduces Fr (333–357 → 293–305 W), preventing over-commitment when the heat-pump is already operating harder under thermally stressful conditions.

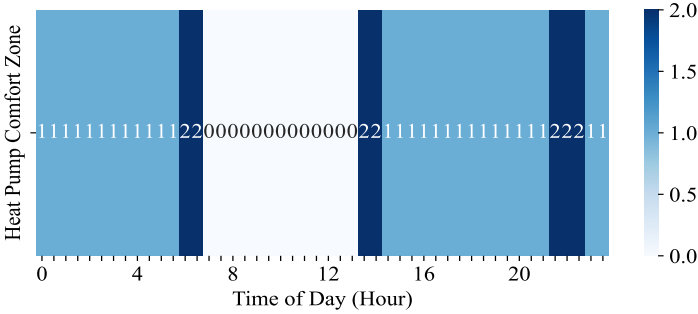


Figure 3.10. Appliance to time association of a heat pump.

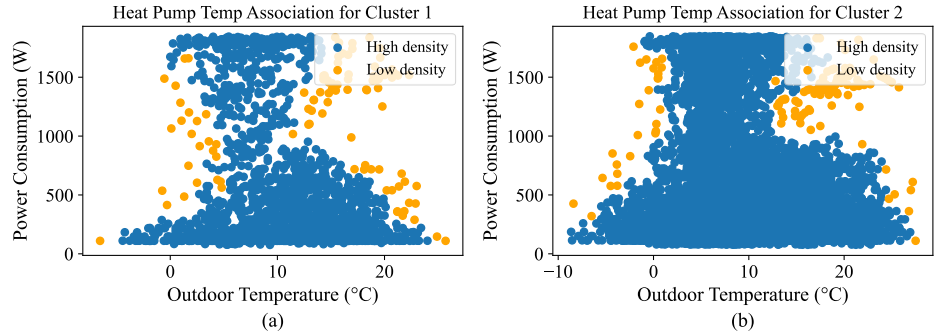


Figure 3.11. Impact of Outside Temperature on Heat Pump Power Consumption for low (a) and high user comfort (b).

Table 3.6. Ramp-Rate Flexibility under Different Temperature Change Scenarios.

Case Study	Comfort	Timestamp	Temperature band [°C]	P_max [kW]	σ [kW]	F_r [kW]
Autumn	High	21:00–22:00	10.10 – 13.90	1.770	0.504	0.333
	Low	22:00–23:00	7.60 – 11.50	1.808	0.415	0.357
Winter	High	21:00–22:00	2.70 – 6.60	1.833	0.689	0.293
	Low	22:00–23:00	2.75 – 6.65	1.843	0.670	0.304

Multidimensional K-means clustering identifies daily battery SoC patterns using outdoor temperature, solar irradiance, and grid-PV contribution. Fig. 3.7 shows the correlation between battery SoC and comfort clusters, highlighting charging during daylight and discharging in high comfort zones, aiding in understanding user battery usage patterns and charged/discharged periods. By examining the battery usage trends and SoC dynamics, the battery variability V_k and hourly adaptability rate α are used to calculate flexibility reserve in each cluster, as shown in Table 3.3. It is observed that during periods of low utilization (cluster 1), the battery has a higher availability of SoC to provide flexibility services. This is attributed to the battery being charged by the solar PV system and the high variability.

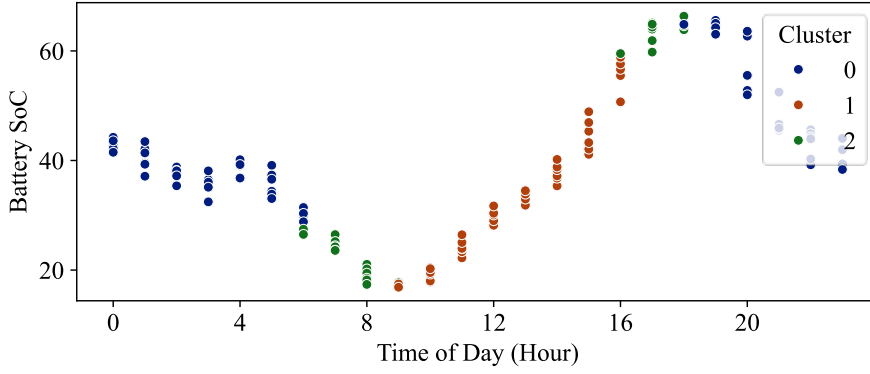


Figure 3.12. Clustered battery usage and SoC patterns.

Table 3.7. Battery Flexibility Reserve Metrics and SoC Availability across Clusters.

Battery Utilization	Time	V_k	Δt	α	F_{res}	F_{Bess} (kWh)
High Utilization	20:00	2.88	2	9.13	6.97	0.697
	00:00		1	2.74	3.55	0.355
	05:00		1	6.06	5.75	0.575
Low Utilization	11:00	5.94	1	4.11	5.32	0.532
	13:00		1	2.80	5.60	0.560
	15:00		1	7.67	13.4	1.34

During High-utilization period (20:00), the larger SoC variation increases the battery's adaptability, yielding 0.697 kWh of available flexibility for the 1-hour market interval. Similarly, during low-utilization (15:00), higher SoC adaptability and comfort-related variability enable the battery to provide 1.34 kWh of flexibility.

3.4.2 Case Study 2: Flexibility Aggregation

After quantifying the flexibility, the aggregation process is performed separately for each appliance type within the households under different comfort zones. For efficient participation in the balancing market for FCR services, a specific 4-hour window from 10:00 to 14:00 is selected, and the maximum available flexibility is evaluated for up-regulation regarding each appliance type for demonstration.

Following the aggregation, the sequential MILP model is applied to optimize the dispatch of this flexibility, providing symmetrical up-regulation and down-regulation while minimizing user discomfort. To elaborate on the total flexibility provided by each appliance type, Fig. 3.8 shows the aggregated appliance-specific contributions.

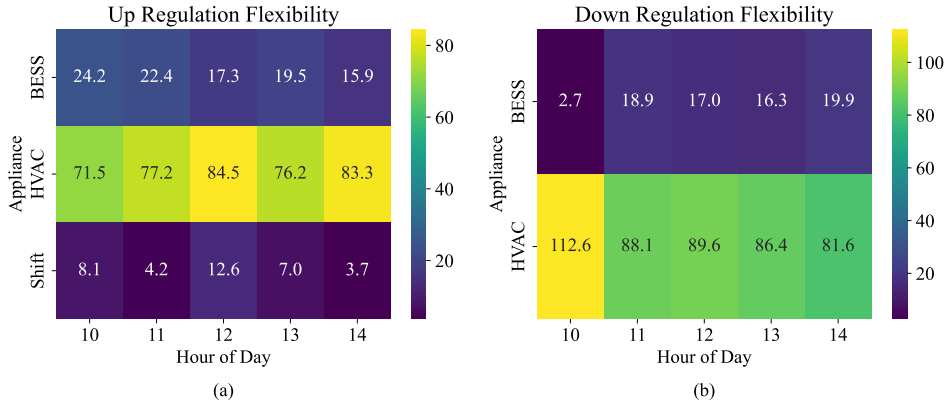


Figure 3.13. Distribution of up-regulation (a) and down-regulation (b) flexibility provided by different appliance types.

Fig. 3.9 highlights the flexibility provision percentage across both comfort zones over the 4-hour period. The low comfort zone, where user comfort is slightly compromised, provides a higher percentage of up-regulation flexibility, averaging around (77-80%), while the high comfort zone's contribution remains around 23%. Similarly, for down-regulation, the average flexibility provision across high and low comfort zones is 85% and 15%, respectively.

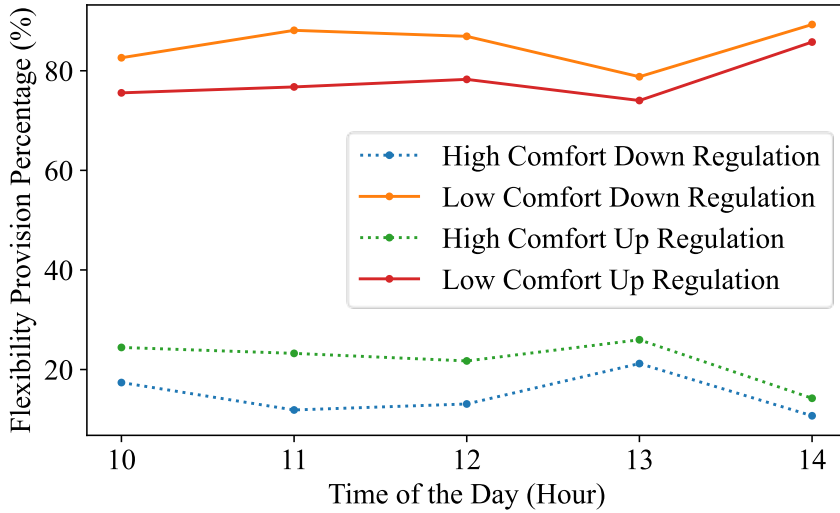


Figure 3.14. Flexibility provision proportions by comfort zone during market bidding slot

3.4.3 Clustering validation and computational scalability

The effectiveness of the proposed methodology is evaluated through two key analyses: clustering performance and optimization scalability. To validate the dynamic comfort zone classification, silhouette score analysis is performed for different numbers of clusters across multiple appliances, including HVAC, BESS, and dishwashers. As shown in Fig. 3.10, the silhouette scores peaked consistently around 3 clusters, confirming the appropriateness of the proposed comfort zone structure. In terms of optimization, the

sequential MILP approach is benchmarked against Particle Swarm Optimization (PSO) to assess scalability. As seen in Table 3.4, the proposed strategy significantly outperformed PSO both in terms of speed and scalability.

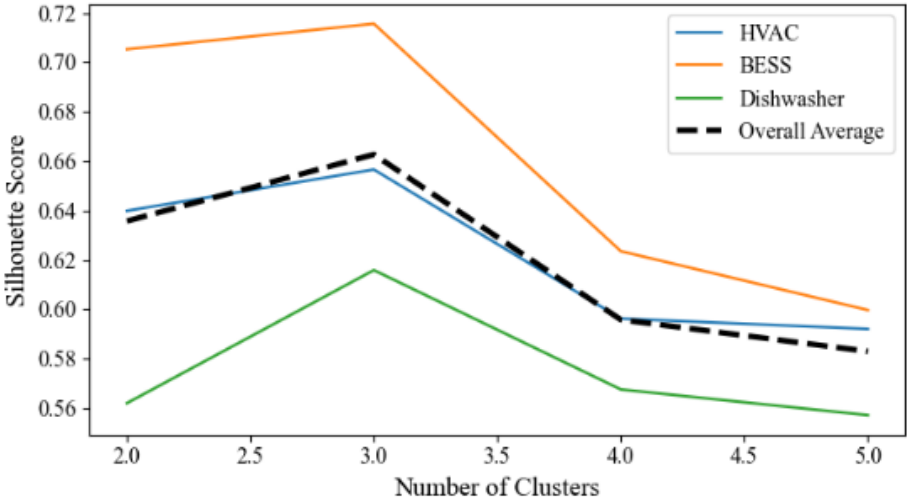


Figure 3.15. Clustering validation across different appliance types

Table 3.4. Comparison of flexibility aggregation optimization performance

Strategies	Scalability	Variables	Constraints	Computational Time
Heuristics (PSO)	150 houses × 4 appliances (4h slots)	18023	12600	23.37 seconds
Proposed				2.20 seconds
Heuristics (PSO)	1,000 houses × 4 appliances (4h slots)	120067	84000	154.28 seconds
Proposed				7.40 seconds

However, clustering quality depends on appropriate historical data length as poor clustering could misclassify comfort zones. Additionally, while the MILP model is highly efficient, it assumes pre-computed flexibility values and does not yet incorporate real-time updates under uncertainty.

3.5 Summary

This chapter presented a complete data-driven framework for quantifying and aggregating residential demand-side flexibility. The proposed method differentiates among three major appliance categories, shiftable appliances, thermostatically controlled appliances, and battery storage systems, and derives flexibility directly from observed behavior, comfort disturbance, weather dependence, and SoC dynamics.

The individual-household case study showed that the method can capture evolving comfort zones, appliance associations, thermal sensitivity, and battery reserve behavior. The community-level case study demonstrated that the resulting flexibility can be

aggregated and optimized to form symmetrical up- and down-regulation products over a defined market window while prioritizing lower-disturbance flexibility.

The quantification and aggregation framework developed in this chapter produces symmetric FCR-N reserve capacity. The resulting reserve envelopes serve as inputs to the forecast-driven market participation framework in Chapter 4, which extends this quantification methodology into a complete market participation pipeline, incorporating transfer learning-based forecasting, market window selection, and real-time coordination for FCR-N delivery. Chapter 5 then addresses the complementary application of aggregated flexibility for distribution-level voltage regulation, demonstrating how the same residential resources can serve multiple grid services through appropriate coordination strategies.

4 Forecast-Driven Aggregation and Real-Time Coordination for Balancing Market Participation

4.1 Introduction

The previous chapter introduced a data-driven methodology for quantifying demand-side flexibility from diverse residential resources. However, transforming this residential potential into a viable product for fast-acting ancillary services, particularly Frequency Containment Reserve for Normal operation (FCR-N), poses significant challenges. To enable forecast-driven aggregation, this chapter introduces a transfer learning-based neural forecasting model; the description of this model is consolidated with the market participation pipeline it directly serves. This chapter presents an end-to-end framework to assist residential aggregators in managing the operational pipeline, from forecasting to real-time coordination and delivery.

The limited participation of residential aggregators in balancing markets, despite the substantial theoretical DSF potential, arises from a combination of technical and operational bottlenecks. As outlined in Chapter 2 (Section 2.3), FCR-N requirements include symmetric capacity, 15-minute market time units (MTUs), prompt activation within minutes of frequency deviations, and a near-linear power-frequency response. Satisfying these criteria with a diverse portfolio of small, behavior-dependent devices is inherently more complex than managing a single large generator.

In this chapter, FCR-N is used as a Nordic benchmark product for fast symmetric frequency regulation. The quantitative compliance results therefore apply to the Nordic/Fingrid FCR-N product settings, including the bid-size threshold, activation timing, droop-response requirements, and delivery-tolerance limits. They should not be interpreted as directly transferable to Estonia, the Baltic balancing capacity market, or the Continental European synchronous area without adapting the formulation to the relevant local product definitions, prequalification rules, telemetry requirements, and minimum bid sizes. The transferable contribution of the chapter is the methodological pipeline for forecasting, market-window selection, risk-aware disaggregation, and real-time coordination of residential flexibility.

The first major bottleneck is the **forecasting of flexibility itself**. Unlike standard load forecasting, which predicts load consumption, flexibility forecasting must predict the adjustable portion of that consumption, a quantity that is not directly observable and is contingent on user comfort, device state, and external factors. As highlighted in the state-of-the-art review (Section 2.4.4), while AI methods like LSTMs and Transformers show promise, they are often trained on aggregated data and struggle to generalise when consumption patterns shift due to behavioral or seasonal changes. Furthermore, for a new aggregator entering a market, the availability of extensive, high-quality historical data for a specific community is rarely guaranteed. This data scarcity renders many ML approaches ineffective, as they require large, representative datasets to avoid overfitting and poor generalization. Therefore, a forecasting methodology is needed that can deliver accurate, community-level flexibility predictions, even when detailed telemetry is available for only a subset of households.

The second critical challenge is formulating a **market-compliant bid**, as steady-state power envelopes do not fully capture the dynamic response capabilities of individual devices. Aggregators cannot simply aggregate flexible power since slow-responding devices, such as HVAC systems, may be unable to provide their full committed power

within the required 60- or 180-second activation windows for FCR-N. Flexibility characterization must incorporate temporal parameters like ramp rates and reaction delays. This requires optimization to translate steady-state forecasts into dynamically deliverable capacity, ensuring bids are technically feasible within the constraints of the devices. Current optimization frameworks often overlook these device-level dynamics, assuming homogeneous portfolios or prioritizing energy arbitrage.

Once a compliant bid is selected, the next bottleneck is **disaggregating the aggregated commitment** to individual households. A simple proportional allocation fails to account for household behavior heterogeneity and device intermittency, leading to potential under-delivery if assigned capacity becomes unavailable during activation. Effective disaggregation must be behavior-aware, leveraging historical availability patterns, and risk-aware, adopting conservative estimates to avoid over-allocating flexibility to volatile resources. Existing frameworks often lack explicit risk quantification, relying instead on deterministic schedules that can falter under real-world uncertainties.

The fourth challenge involves the real-time coordination of resources during activation. Even precise day-ahead forecasts can be erroneous, as devices intended for flexibility may be unavailable, or users may override control signals, leading to discrepancies between expected and actual power delivery [104]. Therefore, the aggregator requires a closed-loop control mechanism capable of detecting and correcting these mismatches within seconds to minutes during an FCR-N activation event. This necessitates rapid, receding-horizon optimization to re-dispatch available resources to meet the droop-based target while adhering to the stringent dynamic performance standards of the balancing product. The literature often separates planning from real-time execution, creating a disconnect that may lead to regulatory non-compliance and financial penalties [81].

Finally, while fulfilling technical and dynamic requirements is paramount, aggregators often operate under the umbrella of a Balance Responsible Party (BRP). A critical, yet often overlooked challenge is managing the economic trade-offs of flexibility activation. Deploying flexibility for frequency regulation alters the local metered load, which can inadvertently increase the BRP's exposure to imbalance penalties. Therefore, this chapter also introduces an integrated economic optimization framework that evaluates the financial trade-offs between internal imbalance management and external FCR-N market participation.

To address these interconnected gaps, this chapter introduces a forecast-driven aggregation and real-time coordination framework for residential aggregators participating in the FCR-N market. The proposed framework is an end-to-end pipeline that systematically tackles each of the bottlenecks described above, building directly upon the quantified flexibility foundation laid out in Chapter 3. The framework encompasses three key components: first, the application of transfer learning from representative households to capture behavioral diversity without necessitating complete community telemetry; second, the implementation of dynamic capability mapping that translates steady-state forecasts into deliverable caps compliant with FCR-N requirements; and third, the establishment of risk-aware hierarchical disaggregation utilizing CVaR-lite caps and eligibility gating. The core contributions of this chapter are:

- **A Transfer Learning-based Multi-Input Multi-Feature Neural Network (TL-MIMF-NN):** This model is developed to forecast community-level flexibility under both low- and high-comfort disturbance conditions. Its key innovation is the use of transfer learning, where the model is pre-trained on data from a small

set of *representative households*—selected via a PCA-K-means behavioural clustering technique—and then fine-tuned on the aggregated community data. This approach generalizes effectively from limited target-domain data, overcoming the data scarcity problem inherent in new aggregator portfolios.

- **A Two-Stage MILP Formulation for Market Participation and Real-Time Coordination:**
 - a) **Stage I (Day-Ahead Market Window Selection):** A Mixed-Integer Linear Programming (MILP) model selects feasible 15-minute participation windows. Its novelty lies in incorporating device dynamics through a *dynamic capability mapping* mechanism, which applies first- and second-order response models to convert steady-state flexibility forecasts into deliverable capacity caps, ensuring compliance with FCR-N activation timelines.
 - b) **Stage II (Real-Time Intra-Interval Coordination):** A second, computationally efficient MILP formulation operates in a closed loop during the 15-minute market interval. Upon detecting a forecast-delivery mismatch, it reallocates flexibility adjustments among available devices to correct the tracking error and meet the droop-based FCR-N target.
- **A Risk-Aware Hierarchical Disaggregation Strategy:** This two-stage strategy translates the aggregated flexibility commitment into executable household setpoints. It is characterized by its:
 - a) **Behavior-Awareness:** It allocates flexibility first to behavioral clusters (derived from the representative household analysis) and then to individual households within those clusters, using availability-weighted driver-energy quantiles.
 - b) **Risk-Awareness:** It employs a Conditional Value-at-Risk (CVaR)-lite cap to bound the assignment to volatile devices and incorporates eligibility gating to exclude inactive resources and minimizes the risk of under-delivery while respecting comfort constraints.
- **Integrated BRP-Aggregator Dual-Role Optimization:** A unified MILP framework that simultaneously optimizes BRP imbalance management and aggregator FCR-N provision, quantifying the systemic trade-offs between internal cost minimization and external market revenue generation.

4.2 Methodology: System Architecture and Forecast-Driven Flexibility Aggregation

The proposed framework is based on the technical specifications of the Nordic FCR-N balancing market product. While numerical values may differ across synchronous areas, the core principles of fast, symmetric, and dynamic response are widely applicable to global fast frequency reserve products. Using FCR-N as a benchmark establishes a robust design foundation. This market acquires symmetrical upward and downward capacity in 15-minute intervals, with a minimum bid size of 0.1 MW. Dynamic performance requirements are stringent: for a ± 0.1 Hz frequency deviation, full activation of contracted capacity is mandated, with at least 63% of power delivered within 60 seconds and 95% within 180 seconds. A near-linear power-frequency droop is also required,

allowing steady-state deviations of -5% to +20% of contracted power. These specifications guide the design of each component in the proposed pipeline.

The aggregator manages a diverse portfolio of residential assets, including HVAC systems, battery energy storage systems (BESS), and shiftable appliances. Flexibility levels are defined as low-disturbance, which allows for broader comfort bands and increased flexibility, and high-disturbance, which involves narrower comfort bands that limit flexibility. Appliance-level flexibility profiles are derived using a data-driven approach that incorporates dynamic comfort zones and technical constraints. The operational workflow consists of four stages: (i) forecasting community-level flexibility from limited household data via transfer learning; (ii) optimizing market participation bids with MILP that includes device dynamics; (iii) disaggregating aggregate bids to individual households through risk-aware hierarchical allocation; and (iv) real-time coordination to ensure delivery of committed flexible power with closed-loop tracking.

4.2.1 Transfer Learning-Based Community-Level Flexibility Forecasting

This section presents a transfer learning-based forecasting approach as shown in Fig. 4.1. The core premise is that while detailed data for an entire community may be scarce, it is feasible to instrument a small, representative subset of households. By learning detailed behavioral patterns from this subset, the model can then generalize to predict the aggregated behavior of the entire community.

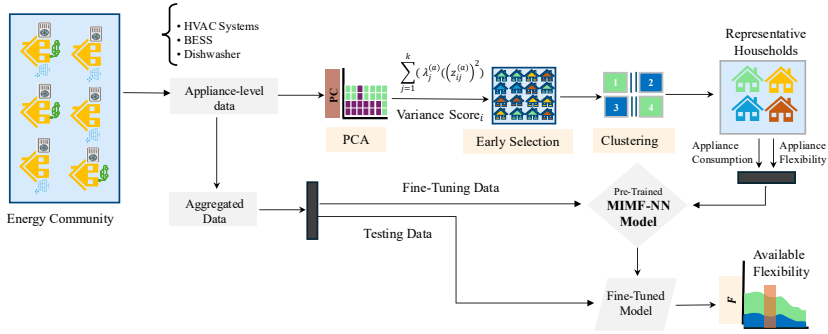


Figure 4.16. MIMF-NN-based transfer learning approach for forecasting aggregated flexibility at the community level [paper X]

The effectiveness of the transfer learning approach relies on the quality of the source domain—the representative households. If the selected households are not truly representative of the community's behavioral diversity, the pre-trained model will learn a biased representation that fails to generalize. To avoid selection bias towards the most common or dominant behavioral patterns, a systematic feature-based selection process is employed for each appliance class $a \in HVAC, BESS, Shiftable$.

First, a comprehensive feature matrix $X^{(a)} \in \mathbb{R}^{n \times m}$ is constructed for all n households in the community. This matrix incorporates a range of statistical and temporal features derived from historical consumption data: mean and variance of consumption during peak/off-peak hours, frequency of appliance starts, operating cycles duration, and correlation of consumption with external factors like temperature or time-of-day.

To reduce the dimensionality of this feature space and identify the dominant axes of behavioral variation, Principal Component Analysis (PCA) is applied:

$$Z^{(a)} = X^{(a)}W^{(a)} \quad (4.1)$$

where $Z^{(a)} \in \mathbb{R}^{n \times k}$ is the projection of the original data onto the first k principal components, and $W^{(a)} \in \mathbb{R}^{m \times k}$ contains the corresponding eigenvectors. The number of components k is chosen to capture a significant portion of the cumulative variance.

To understand each household's contribution to the retained variance, a variance score $V_i^{(a)}$ is calculated:

$$V_i^{(a)} = \sum_{j=1}^k \lambda_j^{(a)} (z_{ij}^{(a)})^2 \quad (4.2)$$

Here, $\lambda_j^{(a)}$ is the eigenvalue associated with the j -th principal component, representing the amount of variance it explains, and $z_{ij}^{(a)}$ is the projection of household i onto that component. This score provides a measure of how "important" or "unique" a household's behavior is within the reduced feature space.

However, selecting households solely based on this variance score could still favor outliers or the most extreme patterns. To ensure a balanced and diverse representation, K-means clustering is performed on the projected data $Z^{(a)}$ to partition the households into K distinct behavioral clusters:

$$\min_c \sum_{j=1}^K \sum_{i \in C_j} \|Z_i^{(a)} - \sigma_j\| \quad (4.3)$$

where C_j represents the set of households in the j -th cluster and σ_j is its centroid. The optimal number of clusters K can be determined using the silhouette analysis on the PCA-reduced data. Finally, the households closest to each cluster centroid are selected as the representative households. This ensures that the training dataset for the source domain contains a diverse cross-section of behaviors from the most common patterns to more distinct ones, providing a robust foundation for transfer learning.

With the representative households identified, the next step is to design a neural network architecture capable of learning the complex, multi-scale temporal dependencies inherent in residential flexibility. The proposed Multi-Input Multi-Feature Neural Network (MIMF-NN) is designed to model these dependencies by processing input features across three temporal horizons: daily, weekly, and monthly.

For a given appliance class, the source domain data consists of input features $X_s^{(a)} \in \mathbb{R}^{T \times d}$ over a forecasting horizon T for the representative households, and the corresponding target flexibility profiles $Y_s^{(a)} \in \mathbb{R}^T$. The input features are carefully engineered to include not only historical consumption data but also exogenous variables that influence flexibility, such as weather data (temperature, solar irradiance), temporal indicators (hour of day, day of week, month), and occupancy patterns.

As illustrated in Fig. 4.2, the MIMF-NN processes these features through three parallel branches, each processing a distinct subset of features:

$$X_d = \{z_t(f) \mid f \in F_d\}, \quad X_w = \{z_t(f) \mid f \in F_w\}, \quad X_m = \{z_t(f) \mid f \in F_m\} \quad (4.4)$$

where F_d , F_w , and F_m are the feature sets for daily (e.g., hour of day, occupancy), weekly (e.g., day of week), and monthly (e.g., month of year, average temperature) time scales, respectively, and $z_t(f)$ is the value of feature f at time t .

Each input branch is processed by a dedicated Bidirectional Long Short-Term Memory

(Bi-LSTM) layer. The choice of Bi-LSTM is motivated by its ability to learn temporal dependencies in both forward and backward directions, providing a richer representation of the sequential context compared to a unidirectional LSTM:

$$\vec{h}_t = \text{LSTM}(X_t, \vec{h}_{t-1}), \bar{h}_t = \text{LSTM}(X_t, \bar{h}_{t+1}) \quad (4.5)$$

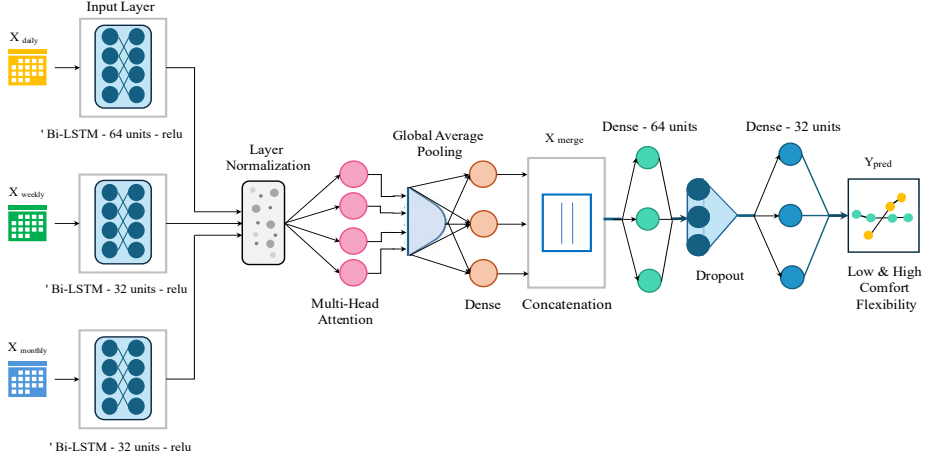


Figure 4.17. Architecture of the proposed transfer learning-based multi-input, multi-feature neural network for aggregated flexibility forecasting [paper X].

The forward and backward hidden states are typically concatenated to form a single output vector for each time step, capturing the full temporal context. To further refine the learned representations and allow the model to focus on the most salient parts of the input sequence, a multi-head attention mechanism is applied to the output of each Bi-LSTM layer:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (4.6)$$

In this formulation, the queries Q , keys K , and values V are derived from the Bi-LSTM outputs. The dot product of queries and keys determines the attention weights, which are then used to compute a weighted sum of the values. The scaling factor $\sqrt{d_k}$ (where d_k is the key dimension) prevents the dot products from growing too large, which could push the softmax function into regions of extremely small gradients. The multi-head mechanism allows the model to jointly attend to information from different representation subspaces at different positions.

The pooled, attention-weighted outputs from the three temporal branches— p_d , p_w , and p_m —are then concatenated into a single, unified feature vector $[p_d, p_w, p_m]$. This rich representation is passed through a series of dense (fully connected) layers with non-linear activation functions to learn high-level interactions between the multi-scale features. The final output layer produces the joint forecasts for both comfort zones:

$$[\hat{y}_{low}, \hat{y}_{high}] = W_o \cdot \sigma(W_f \cdot [p_d, p_w, p_m] + b_f) + b_o \quad (4.7)$$

where W_f and b_f are the weight matrix and bias of the final dense layer, σ is the ReLU activation function, and W_o and b_o are the parameters of the output layer. The two outputs, $\hat{y}_{low}(t)$ and $\hat{y}_{high}(t)$, represent the forecasted community-level available

flexibility under the low-disturbance (C_1) and high-disturbance (C_2) comfort zones, respectively.

The training process follows a transfer learning paradigm. The model is first pre-trained on the source domain data from the representative households. The weights learned during this phase capture general patterns of how flexibility relates to the input features. Subsequently, the model is fine-tuned on the target domain—the aggregated community-level data. During fine-tuning, all layers of the network are updated, but with a lower learning rate, allowing the model to adapt its general knowledge to the specific characteristics of the target community without overfitting to the limited target data. The resulting forecasts for each appliance type and comfort zone serve as the critical inputs to the market participation optimization stage.

4.2.2 Market Participation Optimization (Stage I)

The day-ahead forecasts, $\hat{y}_{low}(t)$ and $\hat{y}_{high}(t)$, define the maximum steady-state power that each appliance type and comfort zone can offer at a given time. However, these steady-state values cannot be bid directly into the FCR-N market because they do not account for the dynamic response characteristics of individual devices. A slow-responding HVAC unit, for example, might be able to provide 2 kW of steady-state flexibility, but it may only be able to deliver 1.5 kW within the first 60 seconds of an activation event. To comply with FCR-N's dynamic requirements, the steady-state forecasts must be converted into dynamically deliverable capacity caps. This conversion is achieved using first- and second-order response models that characterize the activation behavior of different appliance types.

For appliances that exhibit first-order dynamics, such as BESS, the fraction of the target power delivered after time t is given by:

$$f_{first}(t) = 1 - e^{-t/T_b} \quad (4.8)$$

where T_b is the device's time constant. For appliances with more complex, second-order dynamics, such as HVAC systems, the response fraction is:

$$f_{second}(t) = 1 - (Ae^{-t/T_b} + Be^{-t/T_c}) \quad (4.9)$$

where $A = \frac{T_c - T_a}{T_c - T_b}$, $B = \frac{T_a - T_b}{T_c - T_b}$, and T_a , T_b , and T_c are appliance-specific time constants derived from its physical characteristics.

A critical aspect of this methodology is the incorporation of these non-linear device dynamics into a linear optimization framework. This is achieved by applying a dynamic cap to the steady-state flexibility forecast $\widehat{P}_d$ for each device d . This cap, denoted $\bar{P}_d$, ensures that the scheduled power does not exceed what the device can physically deliver within the FCR-N activation timelines. It is calculated by considering the response fraction at the critical 60-second and 180-second checkpoints, and also accounting for a communication delay τ_d :

$$\bar{P}_d = \min_{t \in \{60, 180\}} \left(\frac{f(t - \tau_d)}{\text{Target}_t} \cdot \widehat{P}_d \right) \quad (4.10)$$

Here, $\text{Target}_{60} = 0.63$ and $\text{Target}_{180} = 0.95$ are the FCR-N activation criteria. For example, if a device's model shows it can only deliver 50% of its target after 60 seconds

($f(60 - \tau_d) = 0.5$), then its dynamic cap would be $\bar{P}_d = (0.5/0.63) \cdot \widehat{P}_d$, significantly reducing its schedulable capacity. This mechanism ensures that the MILP formulation works with achievable, rather than theoretical, power values.

The first-stage MILP model is then formulated to determine the optimal set of 15-minute intervals for market participation. For each interval, the model decides which devices to schedule and at what power level, to meet the FCR-N minimum bid size (100 kW) while prioritizing low-disturbance flexibility (C_1) and respecting user comfort limits on C_2 resources.

Let P_d be the scheduled contribution (in kW) of device $d \in D$ in a given 15-minute interval, and let $y_d \in 0,1$ be a binary variable indicating whether device d is selected to participate. The objective function is designed to maximise the total usable flexibility while penalising the use of high-disturbance resources:

$$\max_{P,y} \left(\sum_{d \in C_1} P_d + (1 - \lambda) \sum_{d \in C_2} P_d \right) \quad (4.11)$$

Subject to the following constraints:

$$P_d \leq y_d \cdot \bar{P}_d \forall d \quad (4.11a)$$

$$\sum_d P_d \geq P_{req} = 100 \text{ kW} \quad (4.11b)$$

$$\sum_{d \in C_2} P_d \leq \theta P_{req} \quad (4.11c)$$

$$\begin{cases} D_{up} = \text{HVAC}_{c1}, \text{HVAC}_{c2}, \text{BESS}_{c1}, \text{BESS}_{c2} \\ D_{down} = D_{up} \cup \text{Shiftable}_{c1}, \text{Shiftable}_{c2} \end{cases} \quad (4.11d)$$

In this formulation, $\lambda \in [0,1]$ is a penalty factor for high-disturbance resources, and $\theta = 0.20$ limits their total contribution to the bid. For $\lambda = 1$, only low-disturbance capacity is considered, while smaller λ values allow the use of C_2 resources when necessary to meet the bid requirement. Constraint (4.11a) enforces the device-specific dynamic limits. Constraint (4.11b) ensures the aggregated bid meets the minimum FCR-N capacity. Constraint (4.11c) caps the contribution from high-disturbance resources to protect user comfort. Finally, (4.11d) defines the eligible appliance sets for the symmetrical up- and down-regulation products. Solving this MILP for each 15-minute interval yields a set of market-compliant participation windows and the corresponding day-ahead aggregated flexibility commitment.

4.2.3 Risk-Aware Hierarchical Disaggregation

The day-ahead optimization produces an aggregated flexibility commitment for the entire community. The next challenge is to translate this aggregate signal into specific, executable setpoints for each household. To address this, a two-stage, risk-aware hierarchical disaggregation strategy is proposed. This strategy is behavior-aware, uncertainty-aware, and comfort-aware.

Stage I: Cluster-Level Allocation: In the first stage, households are grouped into the behavioral clusters C_c previously identified via the PCA-K-means analysis in Section 4.2.1.

For each household i in cluster C_c and for each time bin b (e.g., a specific 15-minute interval of the day), a driver-energy signal $X_{i,b}$ (e.g., HVAC consumption, BESS SoC) is observed over a rolling K -day historical window (with $K = 30$). A binary availability indicator $A_{i,b}$ is defined, which is 1 if the driver-energy exceeds a device-class specific noise floor γ (e.g., 0.05 kW for HVAC), and 0 otherwise.

The empirical probability of device i being available in time bin b is then calculated using Laplace smoothing to avoid zero probabilities:

$$p_{i,b} = \frac{\sum_{k=1}^K A_{i,b}[k] + a_o}{K + a_o + b_o}, a_o = b_o = 1 \quad (4.12)$$

This yields $p_{i,b} \in (0,1)$, a robust estimate of availability.

For the days when the device was active ($A_{i,b} = 1$), let $q_{i,b}^{(\alpha)}$ be the α -quantile of the driver-energy signal $X_{i,b}$, conditional on it being above the noise floor. The conditional tail mean, which represents the expected value of the driver-energy below this quantile threshold, is given by:

$$t_{i,b}^{(\alpha)} = \mathbb{E}[X_{i,b} \mid X_{i,b} \leq q_{i,b}^{(\alpha)}, X_{i,b} > \gamma] \quad (4.13)$$

To combine both the typical magnitude of a household's flexibility ($q_{i,b}^{(\alpha)}$) and its reliability ($p_{i,b}$), an availability-weighted quantile mass is defined for the entire cluster:

$$Q_{c,b}^{(\alpha)} = \sum_{i \in C_c} (p_{i,b})^\beta q_{i,b}^{(\alpha)} \quad (4.14)$$

Here, $\beta \in [0,1]$ is a hyperparameter that modulates the penalty for device intermittency. A higher β penalises unreliable devices more heavily, reducing their influence on the cluster's total weighted mass. The normalised cluster participation ratio is then:

$$R_{c,b}^{(\alpha)} = \frac{Q_{c,b}^{(\alpha)}}{\sum_{c'} Q_{c',b}^{(\alpha)}} \quad (4.15)$$

Finally, using these quantile-based ratios, the aggregated flexibility forecast from the MILP stage, $\hat{F}_t^{(low/high)}$, is allocated to each behavioral cluster:

$$\hat{F}_t^{cluster} = R_{c,b(t)}^{(\alpha)} \cdot \hat{F}_t^{(low/high)} \quad (4.16)$$

By construction, this allocation preserves the total energy commitment, as

$$\sum_c \hat{F}_t^{cluster} = \hat{F}_t^{(low/high)} \quad (4.17)$$

Stage II: Household-Level Allocation within Clusters: Within each cluster, the allocation is further refined to the household level. First, eligibility gating is applied: only households that are currently predicted to be active (i.e., those with a non-zero driver-energy probability) are considered. This excludes households with negligible recent activity, making the allocation more relevant and reducing the risk of assigning flexibility to an unavailable resource.

For these eligible households, a quantile-based participation ratio is calculated, which

again weights a household's typical flexibility magnitude by its availability:

$$\rho_{i|c,b}^{(\alpha)} = \frac{(p_{i,b})^\beta q_{i,b}^{(\alpha)}}{\sum_{j \in A_{c,b}} (p_{j,b})^\beta q_{j,b}^{(\alpha)}} \quad (4.18)$$

To prevent over-assigning flexibility to a household with highly variable or uncertain capacity, a CVaR-lite cap is introduced. This cap provides a conservative upper bound on the driver-energy that should be scheduled for that household:

$$u_{i,b}^{(\alpha,\lambda)} = \lambda q_{i,b}^{(\alpha)} + (1 - \lambda) t_{i,b}^{(\alpha)} \quad (4.19)$$

Here, $\lambda \in [0,1]$ is a tunable risk parameter. It interpolates between the α -quantile (a more optimistic estimate) and the tail mean (a more pessimistic, risk-averse estimate). A smaller λ makes the cap more robust to outliers and reduces the probability of under-delivery.

The final household-level setpoint $x_{i,t}$ is then calculated as the minimum of two quantities: (1) its share of the cluster's allocated flexibility based on its participation ratio, and (2) its risk-aware capacity cap, further scaled by availability:

$$x_{i,t} = \min \{ \rho_{i|c,b(t)}^{(\alpha)} \cdot \hat{F}_{c,t}^{cluster}, (p_{i,b(t)})^\eta u_{i,b(t)}^{(\alpha,\lambda)} \} \quad (4.20)$$

The hyperparameter $\eta \in [0,1]$ controls the strength of the availability scaling on the cap. If some households' caps bind, the residual cluster flexibility is redistributed among the remaining eligible households to preserve the cluster target $\hat{F}_{c,t}^{cluster}$.

To ensure the overall disaggregation strategy is robust and has a built-in safety margin, the quantile threshold α is not fixed. Instead, it is chosen adaptively for each timestamp t such that the sum of the risk-aware caps for all eligible households exceeds the total flexibility target by a small margin δ :

$$\sum_{i \in C} (p_{i,b(t)})^\eta \cdot u_{i,b(t)}^{(\alpha,\lambda)} \geq \hat{F}_t^{(low/high)} \cdot (1 + \delta) \quad (4.21)$$

The insurance factor δ is typically set between 0.02 and 0.05, aligning with the $\pm 5\%$ to $+20\%$ steady-state deviation tolerance of the FCR-N market. This adaptive selection of α ensures that the aggregator has a sufficient "buffer" of capacity to draw upon if some households fail to deliver their assigned setpoint. The hyperparameters of this disaggregation framework ($\alpha, \beta, \lambda, \eta, \delta$) are tuned via an offline grid search on historical data, with the objective of maximising the coverage ratio (delivered vs. required energy) while respecting limits on shortfall and over-delivery.

4.2.4 Real-Time Resource Coordination (Stage II)

Following the day-ahead scheduling and disaggregation, the final stage of the framework ensures FCR-N compliance during real-time activation events. Even with accurate forecasts and risk-aware allocation, real-time discrepancies are inevitable. A device may become unavailable, a user might override a control signal, or an unexpected weather event could alter a household's consumption baseline. To manage these mismatches, a closed-loop real-time control system is implemented, as illustrated in Fig. 4.3.

During a 15-minute market interval, the aggregator continuously measures two key values: the target flexibility for each device class f_i^{target} (derived from the disaggregated setpoints) and the actual delivered flexibility $d_i^{act}(t)$. The core of the real-time coordination is a fast, single-cycle MILP optimization that is triggered whenever a significant mismatch is detected. The objective of this optimization is to find the smallest adjustments needed to correct the aggregate tracking error, thereby maintaining compliance with the FCR-N target while respecting the current availability of all devices.

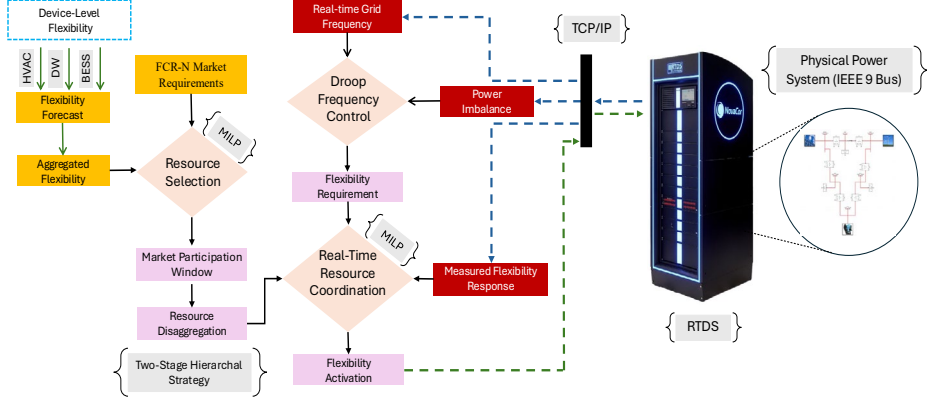


Figure 4.18. Overview of the proposed flexibility aggregation and real-time dispatch framework implemented on RTDS for balancing market participation [paper X]

The real-time MILP is formulated as follows:

$$\min \sum_{i=1}^n x_i \quad (4.22)$$

Subject to:

$$0 \leq x_i \leq a_i(t) - d_i^{act}(t)y_i(t), \forall i \quad (4.22a)$$

$$\sum_{i=1}^n x_i \geq \max \left(0, \sum_{i=1}^n f_i^{target} - \sum_{i=1}^n d_i^{act}(t) \right) \quad (4.22b)$$

$$0.95 P_{steady}(t) \leq P_{agg}(t) \leq 1.20 P_{steady}(t) \quad (4.22c)$$

$$y_i(t) = \begin{cases} 1, & \text{if resource } i \text{ is activated,} \\ 0, & \text{otherwise.} \end{cases} \quad (4.22d)$$

In this formulation, $x_i \geq 0$ is the incremental upward flexibility adjustment requested from device class i to correct an aggregate delivery shortfall. Downward corrections and fine-grained bidirectional tracking are handled separately by the BESS-based droop compensation. Constraint (4.22a) ensures that the new request does not exceed the device's currently available headroom, $a_i(t)$, which is its maximum deliverable power at that instant. Constraint (4.22b) sets the minimum total adjustment required to make up for the aggregate shortfall. Finally, constraint (4.22c) ensures that the new aggregated power $P_{agg}(t)$ remains within the strict -5% to +20% tolerance band of the FCR-N steady-state droop target, $P_{steady}(t)$.

The real-time target $P_{steady}(t)$ itself is not static. It is determined by a frequency-

responsive droop controller that converts the measured grid frequency deviation into a proportional power request:

$$P_{steady} = k_{droop} \cdot \Delta f \quad (4.23)$$

The droop coefficient k is fixed for the duration of a 15-minute market interval and is calculated based on the total committed capacity for that interval. This ensures that the aggregator's response is proportional to the severity of the frequency deviation, as required by the market.

The requested real-time flexibility $\Delta P(t)$ follows a smooth, exponential response characteristic to mimic the behavior of conventional generators and avoid abrupt power swings that could destabilise the grid. This is governed by a first-order response function with saturation at $\pm P_{steady}$:

$$\Delta P(t) = \begin{cases} +P_{steady} \cdot (1 - e^{-t/\tau}), & f \leq 49.9 \text{ Hz} \\ -P_{steady} \cdot (1 - e^{-t/\tau}), & f \geq 50.1 \text{ Hz} \\ k \cdot \Delta f \cdot (1 - e^{-t/\tau}), & f_{db} < |\Delta f| \leq 0.1 \text{ Hz} \\ \Delta P_{prev} \cdot e^{-\Delta t/\tau_{decay}}, & |\Delta f| \leq f_{db} \end{cases} \quad (4.24)$$

Here, τ and τ_{decay} are the activation and decay time constants. When the frequency leaves the deadband f_{db} (typically ± 0.01 Hz), the response ramps towards the steady-state target P_{steady} . When the frequency re-enters the deadband, the response decays smoothly back to zero, preventing sudden disconnection.

In the implemented control hierarchy, the slower-responding assets like HVAC and shiftable loads follow their scheduled setpoints. The BESS, with its fast response time, is used as the primary actuator for real-time correction. The tracking error $e(t)$ is calculated as the difference between the droop-based target and the current aggregated output of all other devices:

$$e(t) = P_{req}(t) - \sum_{i \in \mathcal{A}} P_i(t) \quad (4.25)$$

The BESS command is then updated to compensate for this error:

$$P_{bess}^{cmd}(t) = P_{bess}^0(t) + e(t) \quad (4.26)$$

where $P_{bess}^0(t)$ is the scheduled BESS setpoint from the disaggregation layer, and $P_{bess}^{cmd}(t)$ is the corrected command applied in real-time. This combination of a fast, corrective MILP and a BESS-driven closed-loop tracking mechanism ensures that the aggregator's total response closely follows the FCR-N activation trajectory, even under the uncertainty and variability inherent in a residential portfolio.

4.2.5 Integrated BRP-Aggregator Dual-Role Optimization

While Sections 4.2.1 through 4.2.4 establish the technical framework for flexibility forecasting and real-time coordination, it is equally important to address the economic scheduling of these resources. When an aggregator also assumes the role of a BRP, deploying flexibility for frequency regulation alters the net metered load, directly impacting the BRP's imbalance position. To resolve this trade-off between flexibility

monetization and induced imbalance penalties, an integrated MILP-based co-optimization framework is formulated, as illustrated in Figure 4.4.

The optimization operates within a standard market structure where day-ahead scheduling occurs hourly, while imbalance settlements and FCR-N activations are evaluated at 15-minute imbalance settlement periods (ISPs). For any given interval $k = 1, \dots, N$, if the BRP takes no action, the initial imbalance volume Δ_k is simply the difference between the actual metered load L_k and the forecasted day-ahead load F_k :

$$\Delta_k = L_k - F_k \quad (4.27)$$

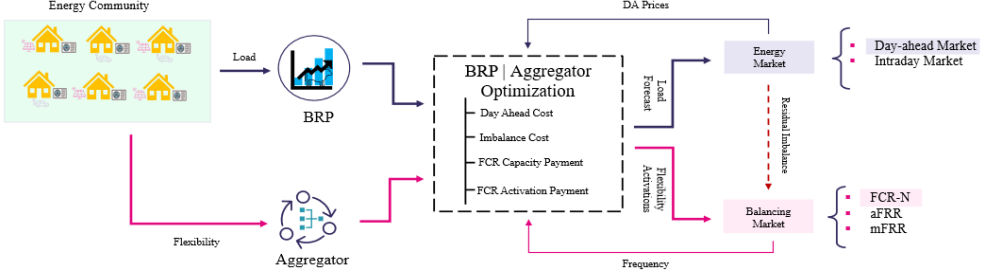


Figure 4.19. MILP-based optimization framework for a BRP-aggregator to minimize imbalance costs [paper VIII].

However, if the BRP commits its aggregated flexibility to the FCR-N market, it must respond to grid frequency deviations. Activating this flexibility R_k^{act} physically alters the metered load. Upward regulation reduces consumption, while downward regulation increases it. This creates a newly adjusted residual imbalance, Δ_k^{adj} :

$$\Delta_k^{adj} = (L_k \pm R_k^{act}) - F_k \quad (4.28)$$

This adjusted imbalance dictates the new penalty the BRP must pay to the Transmission System Operator. Consequently, the ultimate objective of the dual-role optimization is to maximize the total profit across the operational horizon by balancing FCR-N capacity payments C_k^{cap} and activation payments C_k^{act} against the adjusted imbalance settlement costs $C_k^{imb,adj}$:

$$\max_{R_k, U_k, Y_k} \sum_{k=1}^N (-C_k^{imb,adj} + C_k^{cap} + C_k^{act}) \quad (4.29)$$

To thoroughly evaluate this trade-off, the framework analyzes three distinct operational scenarios:

1. **Baseline Scenario:** The BRP deploys no flexibility and absorbs all standard imbalance penalties.
2. **Imbalance Reduction Scenario:** The aggregated flexibility is dispatched exclusively to correct internal forecast errors, minimizing the adjusted imbalance cost without participating in the FCR-N market.

3. **Full FCR-N Market Participation:** Flexibility is fully committed as a reserve. The BRP earns capacity and activation revenues but must absorb the modified imbalance exposure induced by frequency responses.

4.3 Case Study and Validation

4.3.1 Experimental Setup and Validation Framework

The validation environment is designed to replicate a realistic operational setting for a residential aggregator. The power system is modelled using the IEEE 9-bus network implemented in RSCAD/RTDS, which serves as a dynamic testbed capable of generating realistic grid frequency deviations in response to simulated imbalances. RTDS is used to validate the dynamic delivery of the committed FCR-N reserve (the 63% response within 60 s and 95% response within 3 minutes) under closed-loop frequency-response conditions. The optimization stage determines the reserve capacity that can be committed before activation, while the RTDS setup evaluates whether the aggregated residential portfolio can track the required active-power response after frequency deviations.

All forecasting, optimization, and control modules of the residential aggregator are implemented in Python. A real-time communication link is established between the Python-based aggregator and the RTDS simulator via TCP/IP. In this closed-loop configuration, the RTDS computes the grid frequency in real-time based on a representative imbalance scenario. This frequency signal is transmitted to the aggregator, which then computes the required FCR-N activation power based on its droop controller and the current state of its flexible portfolio. The resulting aggregated power response is calculated and fed back to the RTDS as a controllable load, influencing the subsequent grid frequency. This setup enables a holistic evaluation of the entire control chain, from frequency measurement to physical response, within a realistic dynamic environment.

The device-level flexibility profiles, with a 15-minute resolution, are derived from two publicly available datasets: the Pecan Street dataset (USA) and the Cornwall Local Energy Market (LEM) dataset (UK). To create a realistic and statistically significant residential portfolio, a Monte Carlo-based extrapolation is performed, resulting in a community of 150 households equipped with HVAC systems, 100 households equipped with a BESS, and 50 households equipped with a shiftable appliance (dishwasher (DW)).

This specific resource mix is deliberately chosen to test the framework's ability to handle diverse device characteristics. It includes both dominant, predictable resources (HVAC) and fast-responding assets (BESS), alongside intermittent, low-power, and discrete loads (DW). This heterogeneity presents a realistic and challenging test case for forecasting, optimization, and coordination algorithms. To further increase realism, dynamic operating conditions, including variable PV and wind generation profiles, are emulated using publicly available data from Fingrid, the Finnish TSO.

All simulations and model training were performed on a workstation equipped with an Intel Core i7-12700 processor and an NVIDIA RTX 3060 GPU. The MILP optimization problems were solved using the Gurobi optimizer. The key hyperparameters for the forecasting and disaggregation models, which were determined through preliminary experimentation and grid search, are summarized in Table 4.1.

Table 4.8. Summary of Key Framework Hyperparameters

Component	Hyperparameters	Value
MIMF-NN Forecasting	Daily attention heads / key dimension	4 / 32
	Weekly attention heads / key dimension	2 / 16
	Monthly attention heads / key dimension	2 / 16
	Dense layers	64, 32 (ReLU)
	Batch size	32
	Max epochs (pre-train/ fine-tune)	300/200
	Validation split	0.2
	Loss / metric	MSE / RMSE
	Early stopping patience	20
	Recurrent dropout	0.2
	L2 regularization coefficient	1×10^{-4}
	LR scheduler	ReduceLROnPlateau: factor 0.5, patience 10, min_lr 1×10^{-6}
	Learning rate (pre-train / fine-tune)	1×10^{-3} / 5×10^{-4}
Disaggregation (Grid Search)	Look-back window (K)	Recent 30 days
	Risk margin (α)	Candidates {0.2, 0.3, 0.4}; selected 0.2
	Cluster-activation threshold (λ)	Candidates {0.3, 0.5, 0.7}; selected 0.3
	Comfort scaling factor (β)	Candidates {0.3, 0.5, 0.7}; selected 0.3
	Proportionality Coefficient (η)	Candidates {0.4, 0.5, 0.8}; selected 0.5
	Device-class noise floor (γ)	HVAC/BESS: 0.05 kW; DW: 0.10 kW
	Insurance Factor (δ)	0.03 (used in the risk-margin adjustment)
Device Dynamics	HVAC: T_a, T_b, T_c, τ_d	3 s, 7 s, 12 s, 0.5 s
	BESS: T_b, τ_d	0.8 s, 0.05 s
	Shiftable Appliance: T_b, τ_d	1.2 s, 0.20 s

4.3.2 Transfer Learning-Based Forecasting Performance

The forecasting performance of the proposed TL-MIMF-NN is evaluated through a multi-stage validation process. First, the core concept of transfer learning, that a model trained on a small set of representative households can be effectively adapted to the entire community, is validated. A sensitivity analysis is performed using XGBoost as a baseline model to assess the impact of the PCA variance threshold on the number of representative households selected and the subsequent forecasting accuracy. The variance threshold determines how much of the behavioral variance in the feature matrix $X^{(a)}$ must be retained by the principal components. As the results in Table 4.2 show, increasing the threshold from 80% to 95% improves accuracy (RMSE reduces from 18.6 to 12.1) but at the cost of including more households in the representative set (increasing from 18 to 31). A 90% threshold is selected as an optimal trade-off, capturing the predominant behavioral patterns with just 26 households, only 17.3% of the total

community. This confirms the efficiency of the selection process: a small, diverse subset can indeed represent the behavioral variance of the larger population.

Building on this validated threshold, the TL-MIMF-NN is benchmarked against several other modelling approaches for day-ahead forecasting of aggregated HVAC flexibility. The comparison includes: A singular Feed-Forward Neural Network (FF-NN), an N-HiTS model, and an XGBoost-based analysis to compare three strategies: a single aggregated model, a per-household ensemble, and a TL-XGBoost configuration.

Table 4.9. Sensitivity Analysis of PCA Variance Threshold for Representative Household Selection

Variance Threshold	Principal Components	Representative Households	RMSE (kW)
80%	3	18	18.6
85%	4	22	13.4
90%	5	26	12.3
95%	7	31	12.1

The results are presented in Fig. 4.5. The per-household ensemble of XGBoost models achieved the highest theoretical accuracy under high-disturbance conditions (RMSE = 6.42, $R^2 = 0.96$). However, its computational time exceeded one hour, making it completely impractical for real-world operational use. Conversely, the single aggregated model demonstrated poor generalization (RMSE = 12.379 kW, $R^2 = 0.708$), failing to capture the underlying behavioral heterogeneity. The TL-XGBoost approach provided a much better trade-off, achieving comparable accuracy to the single model but with the benefit of transfer learning.

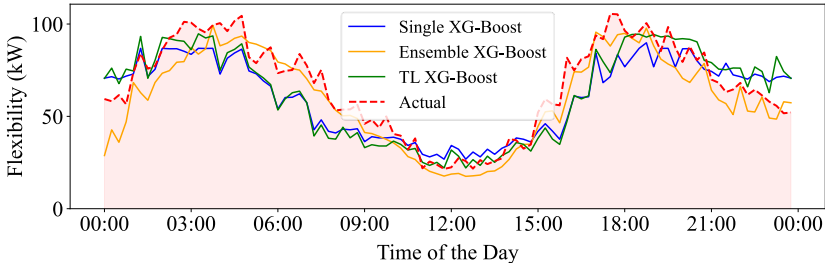


Figure 4.20. Comparison of aggregated HVAC flexibility under the single-aggregate, per-household ensemble, and transfer-learning XGBoost modeling approaches.

The proposed TL-MIMF-NN, however, significantly outperforms all benchmarked models. As highlighted in Table 4.3 and Fig. 4.6, it achieves an NRMSE of 0.092 and an R^2 of 0.925 in the high-disturbance scenario. In the low-disturbance scenario, it achieves an NRMSE of 0.111 and an R^2 of 0.715. This superior performance is attributed to its multi-branch architecture, which explicitly models temporal dependencies at daily, weekly, and monthly scales, and its use of attention mechanisms to focus on the most relevant historical patterns. The total training time for the MIMF-NN, encompassing both pre-training on the 26 representative households and fine-tuning on the full community data, was 1.56 hours, a computationally feasible timeframe for a day-ahead operational model.

Table 4.10. Performance comparison of forecasting models for aggregated HVAC flexibility.

Model	Comfort Zone	Normalized RMSE	R ²
FF-NN	Low comfort disturbance	0.178	0.637
Proposed MIMF-NN		0.111	0.715
N-HiTS		0.146	0.708
FF-NN	High comfort disturbance	0.155	0.786
Proposed MIMF-NN		0.092	0.925
N-HiTS		0.104	0.891

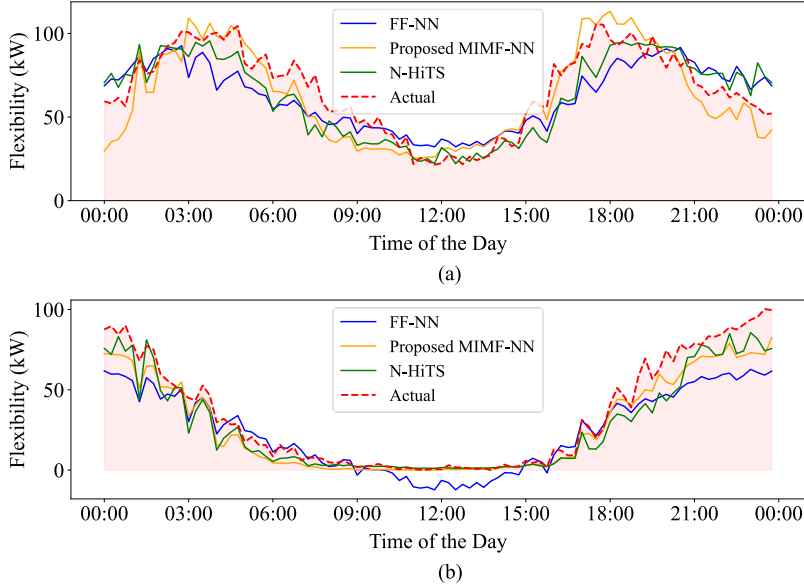


Figure 4.21. Day-ahead aggregated HVAC flexibility forecasts for (a) low and (b) high comfort disturbance zones under different TL-based models.

4.3.3 Market Participation Window Optimization

The forecasted flexibility profiles serve as the primary input to the first-stage MILP optimization, which is responsible for selecting feasible 15-minute participation windows for the following day. For each potential window, the MILP model determines if the 100kW minimum bid requirement can be met while respecting all device-level dynamic constraints and user comfort limits.

A key innovation of this stage is the incorporation of device dynamics through the dynamic cap mechanism described in Equation (4.10). To assess the robustness of this approach, a sensitivity analysis is conducted by varying the time constants of the HVAC systems. These constants (T_b, T_c) are not fixed; they can vary based on ambient conditions, building insulation quality, and occupant behavior. The analysis, summarised in Table 4.4, investigates how uncertainties in these parameters affect the number of feasible market windows.

Table 4.11. Sensitivity of Market Participation to HVAC Time Constant Variations

Parameter Variation	Change in Max. Deliverable Capacity ($\bar{P}_d$)	Feasible Windows (15-min intervals /day)
Nominal Case	0%	18
HVAC (+10%)	-3.5%	17
HVAC (+15%)	-8.2%	15
HVAC (+20%)	-10.1%	12

The results show a clear trend: as the HVAC time constant increases, indicating a slower dynamic response, the dynamically deliverable capacity ($\bar{P}_d$) decreases. This reduction is not linear; a 20% increase in the time constant leads to a 10.1% reduction in deliverable capacity. To meet the 100kW requirement (P_{req}), the MILP must increasingly rely on flexibility from the low-disturbance (C_1) HVAC assets. However, as their effective capacity shrinks, the model is forced to consider resources from the high-disturbance zone (C_2). Constraint (4.11c) strictly limits the contribution from C_2 to 20% of P_{req} to protect user comfort. At the +20% variation point, the deficit in C_1 capacity becomes so large that it cannot be compensated by the allowed 20 kW from C_2 , causing the number of feasible windows to drop sharply from 18 to 12. This analysis highlights the critical importance of accurately modelling device dynamics; an aggregator that ignores this could easily over-bid and face regulatory penalties for under-delivery. The MILP optimization itself is computationally efficient, solving in approximately 0.9 seconds per 15-minute window, making it suitable for day-ahead operational scheduling. Fig. 4.7 illustrates the optimized aggregated flexibility profile for a day, clearly highlighting the specific windows where the FCR-N requirement is met.

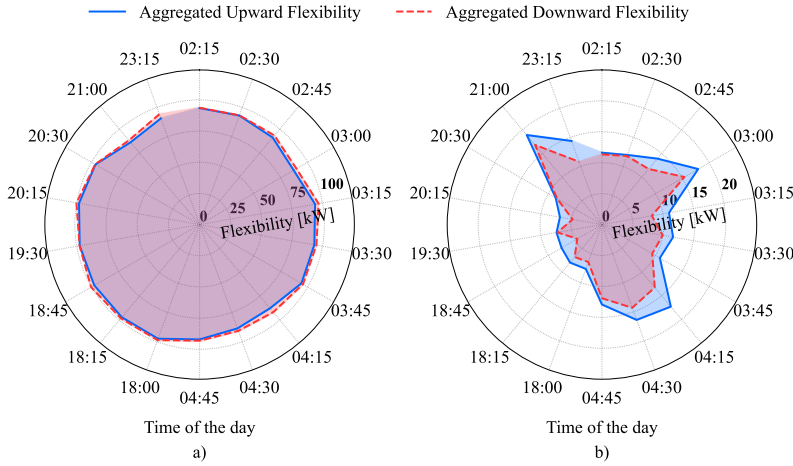


Figure 4.22. MILP-based aggregated flexibility, highlighting the time windows when the aggregator can meet FCR-N balancing-market requirements.

4.3.4 Disaggregation Effectiveness and Resource Allocation

With a market commitment secured for specific 15-minute windows, the next stage is to translate the aggregated flexibility target into actionable setpoints for individual households. The performance of the proposed risk-aware hierarchical disaggregation

strategy is evaluated against a simple proportional allocation baseline. The hyperparameters for the proposed strategy (α , β , λ , η) were tuned via an offline grid search on historical data to maximize the coverage ratio (delivered vs. required energy) while minimizing the fleet-level shortfall.

A quantitative comparison for a representative 15-minute market interval (02:30–02:45) is presented in Table 4.5. The "Required Flexibility" column shows the target derived from the aggregated bid. The "Delivered Flexibility" column shows the sum of the setpoints actually assigned to households after the disaggregation logic is applied. The difference is the "Fleet shortfall," which represents the amount of the required bid that could not be allocated due to household-level constraints.

Table 4.12. Aggregated Required and Delivered Flexibility with Site-Level Error Metrics for Each Appliance, During a 15-Minute Market Interval (02:30–02:45)

Disagg. Technique	Appliance	Required Flexibility (kW)	Delivered Flexibility (kW)	Fleet shortfall (kW)	Sites with Allocation	MAE (kW)	RMSE (kW)
Proportional (Baseline)	HVAC	91.141	84.427	6.714	39	0.172	0.181
	BESS	11.119	9.027	2.091	17	0.122	0.139
	DW	2.182	1.150	1.032	13	0.079	0.086
Risk-Aware Hierarchical (Proposed)	HVAC	91.141	86.551	4.590	31	0.148	0.156
	BESS	11.119	9.827	1.292	14	0.092	0.105
	DW	2.182	1.650	0.532	11	0.048	0.052

The results demonstrate a clear and significant outperformance by the proposed risk-aware strategy. Compared to the proportional baseline, it reduces the fleet-level shortfall by 31.6% for HVAC (from 6.714 kW to 4.590 kW), 38.2% for BESS (from 2.091 kW to 1.292 kW), and 48.5% for DW (from 1.032 kW to 0.532 kW).

The effectiveness of the method in handling intermittent, hard-to-predict resources is particularly evident for DW. The proportional baseline, by naively allocating a share of the DW target to 13 households, results in a large shortfall (1.03 kW). The risk-aware strategy, by contrast, uses its eligibility gating and CVaR-lite caps to allocate the same target to only 11 households—those with higher historical availability and more predictable consumption patterns. This targeted allocation cuts the shortfall nearly in half. The low MAE and RMSE at the site level further confirm that the proposed strategy produces more accurate and reliable individual household setpoints. Fig. 4.8 visually depicts the site-level under-delivery distribution for each appliance type during the same interval, reinforcing the quantitative findings from Table 4.5.

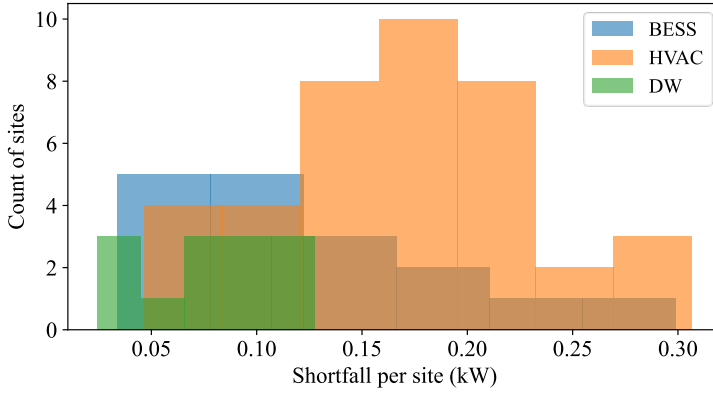


Figure 4.23. Site-level under-delivery distribution for HVAC, BESS, and DW flexibility during 15-minute market intervals (02:30-02:45).

Fig. 4.9 then shows the final output of the second stage: the disaggregated BESS setpoints for a selection of individual households. To validate the quality of these household-level allocations, Fig. 4.10 compares the actual flexible energy delivered by ten representative households against the disaggregated energy target over a three-hour window (02:00–04:59). The close alignment between the actual and disaggregated values confirms that the quantile-based scheme successfully preserves both the aggregate and the underlying household-level energy commitments.

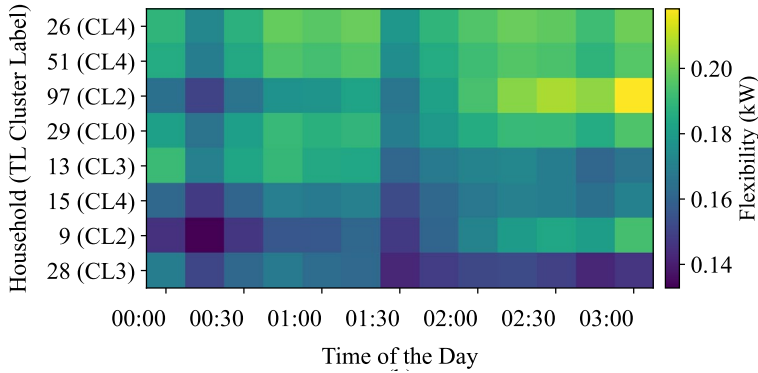


Figure 4.24. Disaggregated BESS flexibility of a few households under high comfort-disturbance zones.

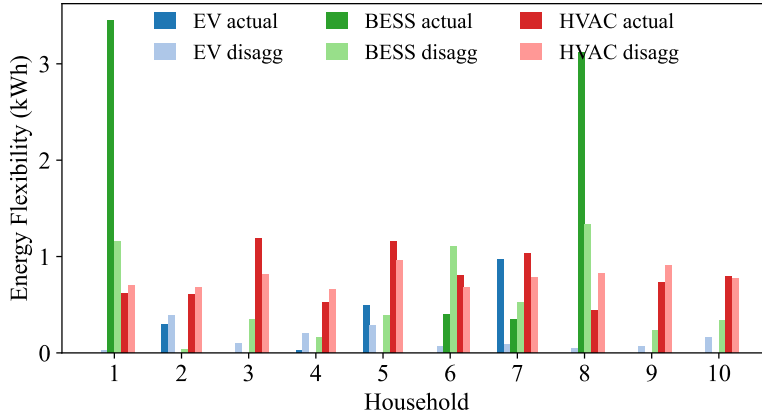


Figure 4.25. Comparison of actual and disaggregated household-level energy flexibility over the 02:00–04:59 window.

4.3.5 Real-Time FCR-N Compliance and Dynamic Performance

The ultimate test of the proposed framework is its ability to deliver the committed FCR-N service in real-time on a dynamic grid. To evaluate this, a 280-second activation event was simulated on the RTDS-based IEEE 9-bus system. During this period, a realistic frequency deviation occurred, requiring the aggregator to provide a total of 2.03 kWh of energy flexibility (corresponding to a mean power of approximately 26.1 kW). The performance of the proportional baseline and the proposed risk-aware disaggregation strategy, when coupled with the real-time coordination layer, is compared in Table 4.6. Fig. 4.11 demonstrates the stabilizing effect on grid frequency.

The proportional baseline, despite day-ahead allocation, under-delivers in real-time, indicating a systematic shortfall of approximately 7.9%. Its high MAE of 3.691 kW and RMSE of 7.510 kW highlight inadequate tracking of the dynamic droop target, risking regulatory non-compliance.

Table 4.13. Comparison of Real-Time Flexibility Delivery Metrics for Proportional and Risk-Aware Disaggregation Techniques on RTDS

Disagg. Technique	Required Energy Flexibility (kWh)		Delivered Energy Flexibility (kWh)		Coverage Ratio	MAE (kW)	RMSE (kW)
	Upward	Downward	Upward	Downward			
Proportional (Baseline)	0.139	-1.893	0.128	-1.743	0.921	3.691	7.510
Risk-Aware Hierarchical	0.139	-1.893	0.141	-1.958	1.033	1.743	3.552

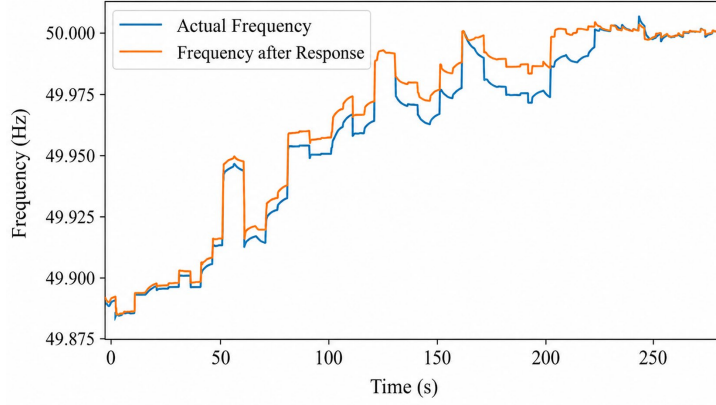


Figure 4.26. Comparison of actual grid frequency and improved frequency after flexibility response simulated on RTDS.

Conversely, the proposed framework utilizing risk-aware disaggregation and real-time coordination achieves a coverage ratio of 1.033, reflecting a slight energy overshoot of 3.3%, well within the $\pm 5\%$ to $+20\%$ steady-state tolerance of the FCR-N market. It rectifies the upward flexibility shortfall from 7.91% to a 1.4% surplus and the downward shortfall from 7.93% to a 3.4% surplus, indicating improved tracking of the droop-based target.

Fig. 4.12 illustrates the real-time power contributions from various resource types, demonstrating how slower HVAC and shiftable loads adhere to scheduled setpoints, while the BESS compensates for tracking errors, ensuring the total response aligns closely with the droop target. Deviations remain within a ± 3 kW band, confirming the effectiveness of the MILP and BESS coordination. The coordination process is computationally efficient, requiring only 0.67 seconds per interval, making it suitable for online applications.

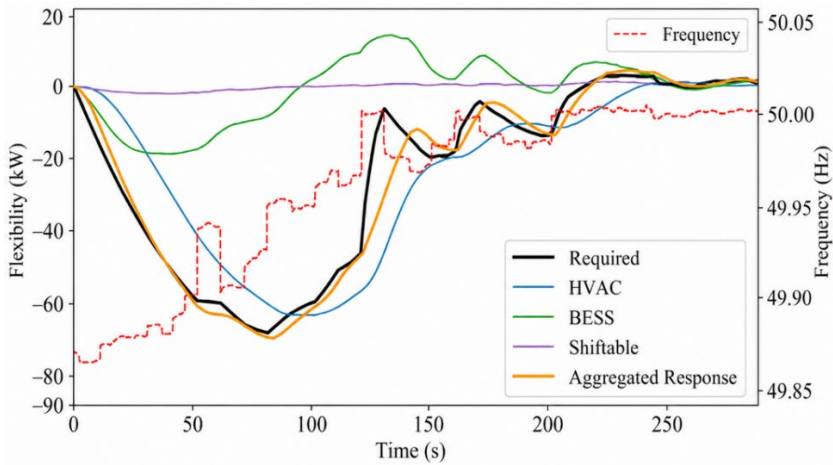


Figure 4.27. Real-time flexibility response of HVAC, BESS, and shiftable loads on RTDS to frequency deviation.

Table 4.7 presents an ablation study isolating the incremental contribution of each disaggregation mechanism. The quantile-based allocation alone reduces shortfall by 13%

(HVAC) by avoiding mean-based over-assignment to volatile devices. Adding eligibility gating improves this to 24% by excluding inactive households. The CVaR-lite cap provides the final 32% reduction for HVAC and 48% for DW, specifically by preventing over-commitment to households with high historical variance. Fig. 4.13 highlights the sensitivity of fleet shortfall and coverage ratio across the $\lambda \in [0,1]$ range.

Table 4.14. Ablation Study of Resource Disaggregation Components

Disagg. Technique	HVAC Shortfall (kW)	BESS Shortfall (kW)	DW Shortfall (kW)	Coverage Ratio
Proportional (baseline)	6.714	2.091	1.032	0.921
Quantile weighting only	5.842	1.756	0.891	0.947
Quantile + Eligibility Gating	5.103	1.534	0.743	0.978
Full proposed	4.590	1.292	0.532	1.033

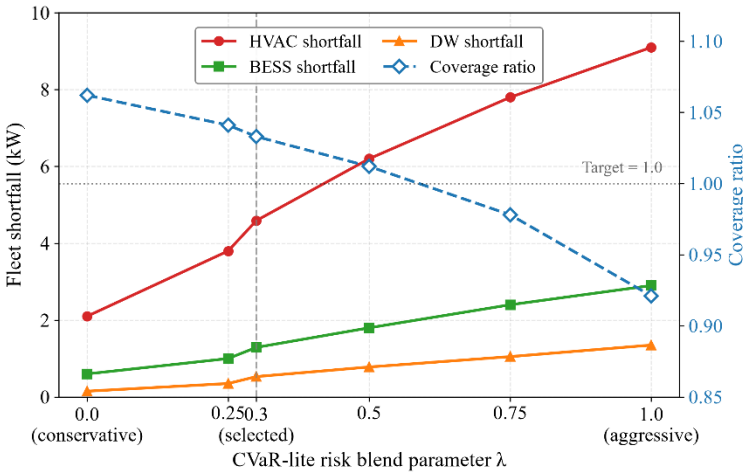


Figure 4.28. Real-time flexibility response of HVAC, BESS, and shiftable loads on RTDS to frequency deviation.

The coverage ratio crosses the target threshold of 1.0 at approximately $\lambda = 0.45$; however, $\lambda = 0.3$ is selected to maintain a safety margin ($\delta = 0.03$) against forecast uncertainty and device intermittency. The figure confirms that the CVaR-lite cap provides a principled continuum between conservative tail-mean allocation ($\lambda = 0$) and aggressive quantile-only allocation ($\lambda = 1$), with the selected value representing the optimal trade-off for FCR-N compliance.

To quantify the propagation of forecasting errors into reserve delivery, we analyze the MIMF-NN forecasts with zero-mean Gaussian noise at 5%, 10%, and 20% of the forecast standard deviation. Table 4.8 shows that the framework maintains coverage ratio greater

than 0.95 up to 10% noise. Real-time MILP coordination compensates for moderate forecast errors by reallocating available BESS capacity and δ safety margin.

Table 4.9 examines how resource mix affects performance. A BESS-dominant portfolio achieves the highest coverage ratio due to fast dynamics, while an HVAC-dominant portfolio struggles with tracking error due to thermal response.

Table 4.10 shows computational runtime as the portfolio scales from 150 to 500 households. The day-ahead MILP solves in less than 2.5 seconds for all sizes due to interval-wise decomposition. The disaggregation scales sub-linearly because cluster-level allocation limits household-level optimization to active clusters only. Real-time MILP remains < 1 second because it operates on resource classes, not individual households.

Table 4.15. Sensitivity of reserve delivery to MIMF-NN forecast degradation

Forecast Noise Level	Coverage Ratio	Mean Tracking Error (kW)	Feasible Windows (/day)
0%	1.033	1.74	18
5%	1.021	2.11	17
10%	0.967	4.45	15
20%	0.934	6.82	11

Table 4.16. Reserve delivery performance across alternative portfolio compositions

Portfolio	HVAC	BESS	DW	Coverage Ratio	Tracking Error (kW)
BESS-dominant	50	100	10	1.045	1.21
HVAC-dominant	150	20	10	0.958	4.20
Mixed (current)	150	100	50	1.033	1.74
DW-heavy	100	50	100	1.012	2.89

Table 4.17. Computational runtime and communication scaling of the proposed framework

Households	Forecast Train (h)	Repr. HHs (90% PCA)	MILP Day-Ahead (s)	Disaggregation (s)	Real-Time MILP (s)
150	1.56	26	0.9	0.3	0.67
300	2.1	41	1.4	0.6	0.71
500	3.2	77	2.1	1.1	0.75

For larger deployments, scalability is supported by the hierarchical structure: forecasting is performed at community, disaggregation is decomposed by behavioral clusters, and real-time corrections operate on active resource classes rather than requiring a monolithic household-level stochastic optimization. In practice, larger portfolios can be handled by parallel cluster-level allocation, rolling-horizon updates, and feeder-level decomposition.

4.3.6 Economic Evaluation of BRP-Aggregator Dual-Role Operation

To quantify the economic viability of the proposed framework, the dual-role optimization was evaluated over a 24-hour horizon using Finnish power system market data. The community load and the technically validated flexibility limits (BESS, shiftable appliances, and HVAC) were scheduled against day-ahead and imbalance settlement prices.

The comparative analysis of the three operational scenarios reveals that dedicating the aggregated flexibility exclusively to the FCR-N market (Scenario 3) yields the most significant economic advantage. As detailed in Table 4.7 and Fig. 4.13, this dual-role strategy achieved a **4.75% reduction** in net operational costs compared to the baseline scenario, outperforming the 0.41% reduction achieved when flexibility was used solely for internal imbalance correction.

Table 4.18. Comparison of Net Operational Costs Under Three Optimization Scenarios

Metric	Scenario 1	Scenario 2	Scenario 3
Net Operational Cost (EUR)	163.50	162.81	155.73
% Cost Reduction vs. Baseline	0	0.41	4.75

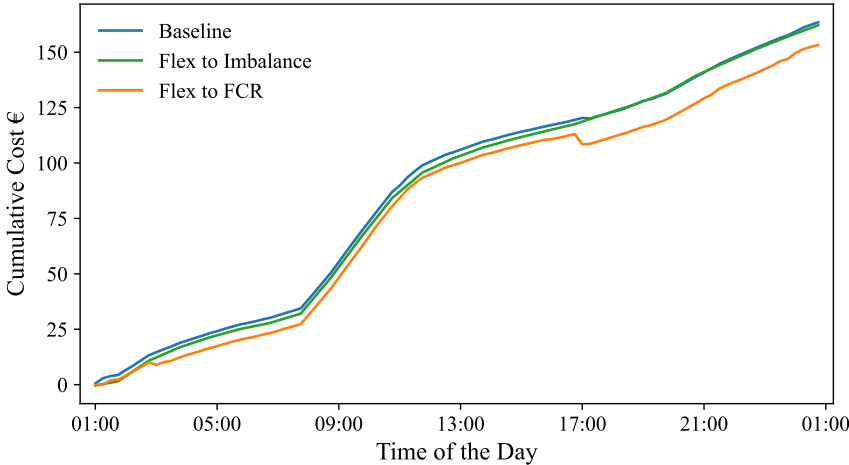


Figure 4.29. Cumulative operational cost comparison highlighting the economic benefit of FCR-N participation.

These savings are primarily driven by substantial FCR-N capacity and activation payments. However, this strategy introduces a critical operational trade-off. As illustrated in Fig. 4.14, frequency-driven flexibility activations reshape the local load profile, occasionally increasing the residual imbalance volume compared to the baseline. Despite these induced imbalance penalties, the revenue generated from the ancillary service market heavily outweighs the costs. This confirms that when demand-side flexibility is coupled with precise forecasting and real-time coordination, it serves as a highly profitable asset for BRPs, provided the systemic risks of residual imbalances are dynamically managed.

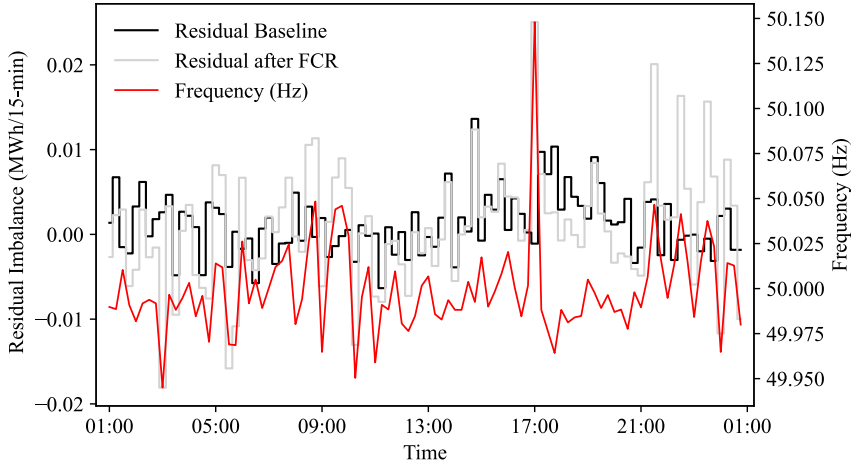


Figure 4.30. Residual imbalances before and after FCR-N flexibility activation based on frequency-responsive control.

4.4 Summary

This chapter has presented an end-to-end framework for enabling residential aggregators to participate in the FCR-N balancing market, addressing four interconnected challenges: forecasting behavior-dependent flexibility with limited data, translating steady-state forecasts into dynamically deliverable commitments, managing under-delivery risk during disaggregation, and correcting real-time forecast-activation mismatches.

The proposed framework integrates four key components. First, a transfer learning-based Multi-Input Multi-Feature Neural Network (TL-MIMF-NN) forecasts community-level flexibility by pre-training on representative households and fine-tuning on aggregated data. This achieves high accuracy (NRMSE 0.092, R^2 0.925) using data from only 17% of households, overcoming data scarcity barriers. Second, a two-stage MILP formulation selects feasible day-ahead market windows through dynamic capability mapping that enforces FCR-N activation timelines, while a real-time stage corrects forecast-delivery mismatches in under 0.7 seconds. Third, a risk-aware hierarchical disaggregation strategy allocates commitments to households using availability-weighted quantiles and CVaR-lite caps, reducing fleet-level shortfall by 31–48% compared to proportional baselines. Fourth, RTDS-based validation on an IEEE 9-bus system demonstrates FCR-N compliance, achieving a coverage ratio of 1.033 and a mean absolute tracking error of 1.74 kW during a 280-second activation event. Finally, the integration of a dual-role BRP-aggregator economic model demonstrated that committing this technically validated flexibility to the FCR-N market is highly viable financially, yielding a 4.75% reduction in net operational costs despite the introduction of frequency-induced residual imbalances.

The service product considered in this chapter is symmetric FCR-N reserve capacity. The aggregator commits reserve capacity in advance, and the real-time controller delivers frequency response during activation. Energy appears only as activation energy and through its effect on BRP imbalance settlement. Therefore, Chapter 4 addresses a market-facing frequency-service application for residential flexibility. Chapter 5 shifts to

a different application: local voltage regulation in active distribution networks. This next application uses the same underlying active-power flexibility resource but does not represent the same market product as FCR-N reserve provision.

5 Deep Reinforcement Learning-Based Model-Free Voltage Regulation in Active Distribution Networks Using Demand-Side Flexibility Aggregation

5.1 Introduction

The integration of distributed energy resources (DERs) such as rooftop PV, BESS, and controllable loads is transforming low and medium-voltage distribution networks from passive systems into active ones, characterized by bidirectional power flows and significant voltage fluctuations. While this shift is crucial for decarbonization, it presents operational challenges that traditional infrastructure cannot effectively address. Conventional voltage regulation, reliant on mechanical devices like on-load tap changers (OLTCs) and capacitor banks, is inadequate for managing the rapid, unpredictable voltage variations associated with high DER penetration.

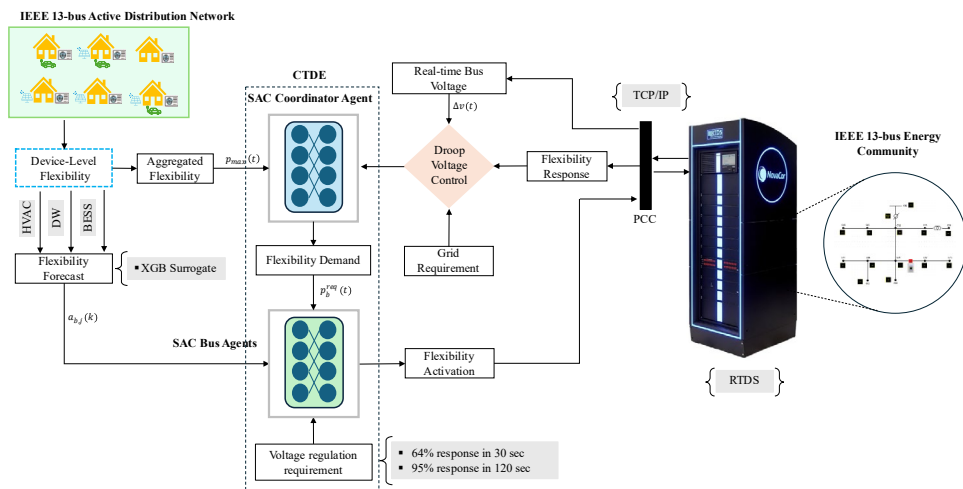
In particular, OLTCs are electromechanical devices with a finite operational lifetime, defined by a limited number of switching operations before requiring maintenance. In modern active distribution networks, frequent voltage fluctuations can lead to a high number of daily tap operations, accelerating mechanical wear and increasing maintenance requirements. For instance, conventional operation may result in tens of tap changes per day, which can accumulate to several thousand operations annually, significantly shortening maintenance intervals and increasing operational expenditure for distribution system operators. OLTC maintenance is typically required after 50,000 to 100,000 operations [105], [106].

The technical root of this challenge lies in the distinct characteristics of distribution networks. Unlike transmission systems, distribution feeders, particularly at low voltage levels, exhibit high R/X ratios, making voltage magnitudes strongly sensitive to active power variations [107]. This physical property creates both a challenge and an opportunity. The challenge is that conventional voltage control strategies, which primarily rely on reactive power support from inverter-based resources, are less effective in these networks. The opportunity is that active power adjustments from demand-side flexibility can provide direct and efficient voltage support.

Despite this theoretical potential, the practical deployment of demand-side flexibility for voltage regulation faces several barriers. Conventional approaches to voltage control in ADNs typically fall into two categories. Optimization-based methods, such as optimal power flow (OPF) and MPC, rely on accurate network models incorporating detailed topology and line parameters [108], [109]. Maintaining such models is challenging for distribution system operators, particularly in secondary feeders where infrastructure evolves and observability is limited. Decentralized droop and rule-based methods respond quickly but lack optimality and cannot coordinate multiple resources for system-wide objectives [110]. Furthermore, many existing approaches focus on supply-side control mechanisms—reactive power management from PV inverters, dispatch of community storage—while overlooking the substantial potential of active-power modulation from flexible loads [111], [112].

Deep reinforcement learning (DRL) has emerged as a promising model-free alternative for voltage regulation, learning control policies directly through environment interaction without requiring explicit grid models. Recent research has demonstrated the

applicability of DRL across various voltage control paradigms, including two-timescale Volt/VAR control [113], [114] safe multi-agent coordination [115], physics-informed learning [116], and central-local coordination architectures [117]. Studies have explored DDPG-based scheduling of electric vehicles for real-time voltage control [118] and DRL frameworks combining PV inverters with district cooling systems [119]. However, much of this literature remains focused on supply-side actuation and often relies on heuristic methods for constraint satisfaction, with limited attention to the systematic coordination of heterogeneous demand-side resources under realistic device dynamics and comfort constraints.



The framework is validated on an RTDS using the IEEE 13-bus radial distribution system, a benchmark network characterized by high R/X ratios and strong coupling between active power and voltage. Realistic disturbances are introduced using real-world wind speed and solar irradiance profiles from Fingrid, driving dynamic

renewable generation and associated voltage fluctuations. The performance of the proposed hierarchical SAC architecture is evaluated against conventional strategies (OLTC-only control, flexibility-only control) and benchmarked against alternative DRL algorithms (TD3, DDPG, PPO).

The main contributions of this chapter are:

- **A Hierarchical CTDE-MADRL Architecture for Model-Free Voltage Regulation:** The proposed framework couples adaptive droop tracking with implicit sensitivity learning, enabling context-aware allocation of flexibility requests across load buses without requiring network topology, line parameters, or explicit sensitivity calculations. This represents a significant advancement over both optimization-based methods (which require accurate models) and fixed allocation heuristics (which cannot adapt to operating-point-dependent sensitivities).
- **Surrogate-Embedded Constrained DRL with Feasibility Enforcement:** The integration of XGBoost-based flexibility forecasting with SAC policies and bounded-simplex quadratic programming projection ensures that all setpoints are physically realizable and respect device dynamics. This addresses a critical limitation of pure DRL approaches, which often generate infeasible actions that cannot be executed in practice.

5.2 Methodology

This section presents the proposed hierarchical, model-free control framework for real-time voltage regulation in active distribution networks using aggregated residential demand-side flexibility. The methodology is designed to operate without any knowledge of network topology or line parameters, relying solely on a single-point voltage measurement at the point of common coupling (PCC) and surrogate-based forecasts of per-appliance flexibility availability. The architecture follows a Centralized Training with Distributed Execution (CTDE) paradigm, comprising two learning layers: a top-level coordinator agent that translates PCC voltage deviations into bus-level flexibility allocations, and distributed bus agents that disaggregate these allocations into feasible appliance-level setpoints while respecting device dynamics and grid response requirements.

5.2.1 System Architecture Overview

The proposed control framework is designed for an energy community connected to an active distribution network. Let B denote the set of controlled buses, and for each bus $b \in B$, let $J_b = \text{HVAC, BESS, DW}$ be the set of controllable residential resources. At timestamp t , the target-bus voltage is $v(t)$, while the realized and setpoint powers (kW) for device $j \in J_b$ at bus b are $y_{b,j}(t)$ and $u_{b,j}(t)$, respectively. The surrogate-predicted per-appliance availability is expressed as $a_{b,j}(k)$ for each 15-min interval k and is internally smoothed at 1 Hz to $\bar{a}_{b,j}(t)$. Aggregated bus and system-level flexibility outputs are defined as:

$$y_b(t) = \sum_{j \in J_b} y_{b,j}(t), y_{\text{tot}}(t) = \sum_{b \in B} y_b(t) \quad (5.1)$$

The control objective is to maintain the PCC voltage within acceptable limits by dynamically adjusting the active power consumption of flexible resources, while minimizing reliance on mechanical OLTC operations and ensuring that all setpoints are feasible given device constraints and availability.

5.2.2 Surrogate Flexibility Forecasting

A critical prerequisite for effective voltage control is accurate knowledge of the available flexibility at each bus and for each appliance. Each bus agent incorporates a lightweight XGBoost-based surrogate model that forecasts short-term, per-appliance flexibility availability.

For each appliance (b, j) , an XGBoost regressor $f_{b,j}^{\text{XGB}}$ is trained to map a feature vector $x_{b,j}(k)$ to the predicted available flexibility for the next 15-minute interval k . The feature vector includes:

- Temporal features: time-of-day, day-of-week, season
- Historical usage: recent appliance consumption patterns
- Exogenous variables: external temperature for HVAC, state of charge for BESS
- Behavioral patterns: typical usage windows derived from historical data

The forecasting relationship is expressed as:

$$a_{b,j}(k) = f_{b,j}^{\text{XGB}}(x_{b,j}(k)) \quad (5.2)$$

Since the control loop operates at 1 Hz while flexibility forecasts are generated at 15-minute intervals (96 intervals per day), a discrete-time first-order filter is applied to smooth the step changes between intervals and provide continuous availability estimates:

$$\bar{a}_{b,j}[k+1] = \bar{a}_{b,j}[k] + \frac{T_s}{T_{\text{lim}}} (a_{b,j}(k) - \bar{a}_{b,j}[k]) \quad (5.3)$$

where $T_s = 1$ second is the sampling period and T_{lim} is the smoothing horizon (set to 30 seconds in this study). This filtering prevents abrupt changes in availability estimates that could lead to control instability.

The system-wide instantaneous flexibility cap, which bounds the total active power that can be modulated at any time, is then:

$$p_{\text{max}}(t) = \sum_{b \in B} \sum_{j \in J_b} \bar{a}_{b,j}(t) \quad (5.4)$$

This time-varying cap serves as a critical constraint for the coordinator agent when generating aggregate flexibility requests.

5.2.3 Coordinator Agent Design

The coordinator agent is responsible for translating observed PCC voltage deviations into an aggregate active-power flexibility request and distributing this request across the controlled buses. The agent operates without any knowledge of network topology or line parameters; instead, it learns an implicit mapping from voltage deviations to effective bus-level allocations through repeated interactions during training.

The first stage of the coordinator's operation converts the voltage deviation $\Delta v(t)$ into a raw aggregate flexibility target using an adaptive droop

controller. The droop gain at time t is scaled by the system-wide flexibility cap $p_{\max}(t)$ to ensure that requests remain within physically achievable bounds:

$$K_d(t) = \frac{p_{\max}(t)}{\Delta V_{\text{sat}}}, \Delta V_{\text{sat}} = 0.05 \text{ p.u.} \quad (5.5)$$

The saturation voltage ΔV_{sat} defines the deviation at which the controller requests the full available flexibility. The saturated droop target is:

$$p(t) = \text{sat}_{[-p_{\max}(t), p_{\max}(t)]}(K_d(t)\Delta v(t)) \quad (5.6)$$

To avoid excessive mechanical wear on appliances and to provide a smooth response, the raw target $p(t)$ is passed through an adaptive first-order filter that generates the actual aggregate request $p_{\text{req}}(t)$. The filter incorporates a deadband around nominal voltage to prevent unnecessary activations:

$$\alpha_k = 1 - e^{-\frac{T_s}{\tau(|\Delta v(t)|)}} \quad (5.7)$$

$$\tau(|\Delta v(t)|) = \tau_{\max} - (\tau_{\max} - \tau_{\min}) \cdot \min\left(\frac{|\Delta v(t)|}{\Delta V_{\text{sat}}}, 1\right), \quad (5.7a)$$

$$p_{\text{req}}(t+1) = \begin{cases} p_{\text{req}}(t) \cdot e^{-T_s/\tau_{\text{decay}}}, & |\Delta v(t)| \leq v_{\text{db}} \\ p_{\text{req}}(t) + \alpha_k (p(t) - p_{\text{req}}(t)), & \text{otherwise} \end{cases} \quad (5.8)$$

The time constant τ is dynamically adjusted based on the voltage deviation magnitude, decreasing near nominal voltage for faster deactivation and increasing near saturation to prevent overshoot. The decay time constant τ_{decay} (120 second) governs the smooth return to zero when voltage re-enters the deadband.

These parameters shape the closed loop as follows. **Stability:** the gain $K_d(t)$ is bounded by the available flexibility, the request is saturated to $\pm p_{\max}(t)$, and with a 1-second control step and $\tau \geq 5$ s, the discrete update gain $\alpha_k \leq 0.18$, yielding a well-damped first-order response; the deadband prevents cycling around nominal voltage. **Tracking speed:** large deviations are corrected on a ≈ 5 s timescale. The request reaches over 99% of the droop target within 30 s, so the reference leads the dynamic-response envelopes of Eq. (12), and the binding constraint is device physics rather than reference shaping, while deviations just above the deadband are tracked with τ up to 40 s to avoid unnecessary adjustments. **Comfort:** the deadband suppresses actuation for $|\Delta v| \leq 4$ V, the slow tracking of minor deviations extends this protection continuously above the deadband edge and limits unnecessary device cycling, and the geometric in-deadband decay returns devices to baseline without abrupt cycling, which also suppresses short-term rebound by preventing simultaneous release and re-activation of resources.

Once the aggregate request $p_{\text{req}}(t)$ is determined, the coordinator must decide how to distribute this request across the controlled buses. This is a critical task because different buses have different sensitivities to active power injections. In a model-based approach, these sensitivities would be derived from the network Jacobian; in this model-free framework, they must be learned.

The coordinator employs a Soft Actor-Critic (SAC) policy π_c that maps a global observation vector $o_c(t)$ to an allocation vector $r(t) = [r_b(t)]_{b \in B}$, where each $r_b(t)$ represents the fraction of the aggregate request assigned to bus b , satisfying $\sum_{b \in B} r_b(t) = 1$. The bus-level requests are given by:

$$p_b^{\text{req}}(t) = r_b(t) \cdot p_{\text{req}}(t) \quad (5.9)$$

The key insight enabling model-free learning is that the coordinator can infer the voltage–power sensitivity of each bus by observing how its allocation decisions affect the resulting PCC voltage. Through repeated episodes during training, the SAC agent learns to associate specific allocation patterns with their voltage correction outcomes, gradually building an implicit, operating-point-dependent sensitivity model. Buses that consistently provide stronger voltage response per unit of allocated flexibility receive higher allocations when voltage deviations are large, while buses with weaker sensitivity or tighter availability constraints receive proportionally less.

The coordinator's reward function is designed to incentivize accurate voltage tracking while penalizing excessive reallocation between buses that could cause instability or mechanical wear:

$$r_{\text{cord}}(t) = -|\Delta v(t)| - \frac{|p_{\text{req}}(t) - y_{\text{tot}}(t)|}{\max\{1, |p_{\text{req}}(t)|\}} - \lambda_c \sum_{b \in B} (r_b(t) - r_b(t-1))^2 \quad (5.10)$$

The first term penalizes voltage deviations from the nominal. The second term penalizes a mismatch between the requested aggregate flexibility and the total delivered flexibility, encouraging the coordinator to generate requests that are achievable given the available resources. The third term penalizes rapid changes in the allocation vector, promoting smooth transitions that reduce stress on downstream appliances.

5.2.4 Load Bus Agent Design

Each bus agent receives an allocated flexibility request $p_b^{\text{req}}(t)$ and the per-appliance availability forecasts $\bar{a}_{b,j}(t)$, and must determine feasible setpoints $u_{b,j}(t)$ for its local resources. This task is complicated by three factors: (1) the heterogeneous dynamic responses of different appliance types, (2) strict grid response requirements that must be satisfied dynamically, not just in steady state, and (3) hard feasibility constraints that cannot be violated.

To ensure that setpoints are physically realizable, each bus agent incorporates models of appliance dynamics. These models are used during training to simulate the response of each resource and during execution to verify that setpoints will lead to compliant behavior.

For HVAC systems, which exhibit thermal inertia and second-order dynamics due to the coupling between air temperature and building mass, the response is modelled as:

$$\ddot{y}_{b,\text{HVAC}}(t) + 2\zeta\omega_n\dot{y}_{b,\text{HVAC}}(t) + \omega_n^2 y_{b,\text{HVAC}}(t) = \omega_n^2 u_{b,\text{HVAC}}(t) \quad (5.11)$$

where ζ is the damping ratio and ω_n is the natural frequency, calibrated from typical HVAC response characteristics. For BESS and shiftable loads (dishwashers), which exhibit first-order lag dynamics, the response is modelled as:

$$\tau_j \dot{y}_{b,j}(t) = -y_{b,j}(t) + u_{b,j}(t), j \in \text{BESS, DW} \quad (5.12)$$

where τ_j is the time constant for each appliance type.

To ensure that the aggregated flexibility from each bus provides useful voltage support, the delivered response must meet dynamic performance requirements. These requirements are adapted from the FCR-N balancing market specifications used in Chapter 4 but scaled to the faster dynamics expected in distribution-level voltage control. Specifically, the total delivered flexibility at each bus must achieve at least 64% of the absolute requested value within 30 seconds, and 95% within 120 seconds:

$$y_b(t + 30 \text{ s}) \geq 0.64 \mid p_b^{\text{req}}(t) \mid, y_b(t + 120 \text{ s}) \geq 0.95 \mid p_b^{\text{req}}(t) \mid \quad (5.13)$$

These envelope constraints are implemented through penalty terms in the bus-agent reward function during training. Slack variables $s_{b,30}(t)$ and $s_{b,120}(t)$ track the shortfall from these requirements at each time step.

A critical innovation in this framework is the integration of hard feasibility constraints directly into the action generation process. Pure DRL policies often produce actions that are infeasible in practice. For example, requesting more power from a BESS than its current state of charge allows, or commanding an HVAC setpoint that would violate comfort constraints. To address this, the bus agent's raw action $z_{b,j}(t)$ from the SAC policy is projected onto the feasible set through a quadratic programming (QP) layer.

First, to provide robustness against surrogate forecast errors and random appliance unavailability, the bus-level request is adjusted by a buffer margin β (determined through sensitivity analysis as 5%):

$$\bar{p}_b^{\text{req}}(t) = \begin{cases} (1 + \beta)p_b^{\text{req}}(t), & p_b^{\text{req}}(t) > 0 \\ (1 - \beta)p_b^{\text{req}}(t), & p_b^{\text{req}}(t) < 0 \\ 0, & p_b^{\text{req}}(t) = 0 \end{cases} \quad (5.14)$$

If the buffered request exceeds the aggregate available flexibility at the bus, it is saturated to $\pm \sum_j \bar{a}_{b,j}(t)$. Any remaining shortfall is treated as unavoidable and reflected in the reward penalties.

The QP projection then finds the set of appliance setpoints $u_{b,j}(t)$ that are closest to the raw SAC actions $z_{b,j}(t)$ while satisfying two constraints: (1) the sum of setpoints must equal the buffered request, and (2) each setpoint must lie within its per-appliance availability bounds:

$$\min_{\{u_{b,j}(t)\}_{j \in J_b}} \sum_{j \in J_b} (u_{b,j}(t) - z_{b,j}(t))^2 \quad (5.15)$$

subject to:

$$\sum_{j \in J_b} u_{b,j}(t) = \bar{p}_b^{\text{req}}(t) \quad (5.15a)$$

$$-\bar{a}_{b,j}(t) \leq u_{b,j}(t) \leq \bar{a}_{b,j}(t), \forall j \in J_b \quad (5.15b)$$

This is a bounded-simplex projection that can be solved efficiently using standard QP solvers.

The bus agent's reward function incentivizes accurate tracking of the allocated request, compliance with dynamic response envelopes, and smooth control actions:

$$r_{bus}(t) = -\frac{|\bar{p}_{req}(t) - y_b(t)|}{\max\{1, |\bar{p}_{req}(t)|\}} - \mu_{30} s_{b,30}(t) - \mu_{120} s_{b,120}(t) - \eta \sum_{j \in J_b} (u_{b,j}(t) - u_{b,j}(t-1))^2 \quad (5.16)$$

The first term penalizes tracking error. The second and third terms penalize shortfalls from the 30-second and 120-second response requirements. The fourth term penalizes rapid fluctuations in setpoints to reduce mechanical wear and improve user comfort.

5.2.5 Reinforcement Learning Formulation

Both the coordinator and bus agents are trained using the Soft Actor-Critic (SAC) algorithm under the CTDE framework. SAC is chosen for its sample efficiency, stability, and ability to handle continuous action spaces through maximum entropy reinforcement learning, which encourages exploration and prevents premature convergence to poor policies.

During training, all agents have access to global information, including the full state of all buses and the actual voltage outcomes of their joint actions. This allows the coordinator to learn how its allocation decisions influence the final voltage trajectory, and allows each bus agent to learn how its local actions contribute to meeting its allocated request while respecting dynamic constraints.

The training process proceeds as follows:

- **Environment Interaction:** At each timestep, the coordinator observes its global state $s_c(t)$ and samples an action $r(t) \sim \pi_c(\cdot | s_c(t))$. This action is transformed into bus-level requests via Equation (5.9). Each bus agent observes its local state $s_b(t)$ (including its allocated request and local availability) and samples raw actions $z_b(t) \sim \pi_b(\cdot | s_b(t))$. These raw actions are projected through the QP layer to produce feasible setpoints $u_b(t)$, which are applied to the simulated appliance dynamics to generate realised powers $y_b(t+1)$ and a new PCC voltage $v(t+1)$.
- **Experience Storage:** The transition $(s_c(t), r(t), s_c(t+1), r_{cord}(t))$ is stored in the coordinator's replay buffer. Similarly, transitions $(s_b(t), z_b(t), s_b(t+1), r_{bus}(t))$ are stored in each bus agent's replay buffer. The stored action is the raw SAC action $z_b(t)$, not the projected setpoint $u_b(t)$. This ensures that the policy learns to propose actions that are close to the feasible region.
- **Policy Update:** Periodically, mini-batches are sampled from each replay buffer to update the SAC policies and value functions. The SAC algorithm maximizes a trade-off between expected return and policy entropy, with the temperature parameter automatically adjusted to achieve a target entropy.

After training, the agents are deployed for execution with only local information. The coordinator observes the PCC voltage and its own local features (smoothed per-bus availability bounds) to generate allocations. Each bus agent observes its allocated request and local availability to generate setpoints. There is no communication between agents during execution, and no global optimization is performed, all decisions are made locally based on learned policies.

5.3 Case Study and Validation

5.3.1 Experimental Setup and Validation Framework

The validation environment is designed to replicate a realistic operational setting for an energy community participating in distribution-level voltage support. The power system is modelled using the IEEE 13-bus radial distribution network implemented in RTDS. This benchmark system is characterized by its high resistance-to-reactance (R/X) ratios, unbalanced loading, and strong coupling between active power and voltage—properties that make it particularly suitable for evaluating active-power-based voltage regulation strategies.

The IEEE 13-bus system includes a substation transformer with an on-load tap changer (OLTC) capable of 20 tap positions, ranging from 0.766 p.u. to 1.30 p.u. Spot loads are distributed across the network, with a subset designated as flexible. Similarly, distributed generation sources (PV and wind) are connected at multiple buses, and are driven by real-world weather profiles

Three load buses (Bus 1, Bus 5, and Bus 6) are designated as flexibility hubs, each aggregating HVAC, BESS, and DW resources from the residential community. Each bus agent runs as an independent Python process, exchanging setpoints with RTDS via TCP/IP at 1 Hz. The coordinator agent also runs as a separate process, receiving voltage measurements from the PCC and transmitting allocation vectors to the bus agents. Device-level flexibility profiles are derived from the same datasets used in Chapter 4.

All DRL agents are trained on an Intel Core i7-12700 workstation with an NVIDIA RTX 3060 GPU (12 GB VRAM). Training employs 11 parallel environments to accelerate experience collection, with 1 million total steps completed in approximately 1.5–2 hours. Peak GPU memory usage remains below 1 GB, indicating a modest memory footprint that supports practical deployment on commodity hardware.

The buffer margin $\beta = 0.05$ (5%) is selected through sensitivity analysis, balancing robustness to XGBoost forecast errors against flexibility utilisation. Analysis shows that $\beta = 5\%$ reduces constraint violations from 8.2% to 1.3% while imposing only a 2.4% conservatism penalty, representing the Pareto-optimal trade-off. Table 5.1 summarizes the key simulation and learning hyperparameters adopted throughout the validation.

For bus agent evaluation, the proposed SAC-based approach is benchmarked against three alternative DRL algorithms: TD3 (Twin Delayed DDPG), DDPG (Deep Deterministic Policy Gradient), and PPO (Proximal Policy Optimization)

For coordinator evaluation, the learned SAC allocation policy is compared against a fixed capacity-proportional allocation baseline, where the aggregate request is distributed among buses in proportion to their instantaneous total available flexibility:

$$r_b(t) = \frac{\bar{a}_b(t)}{\sum_{i \in B} \bar{a}_i(t)}, p_b^{\text{req}}(t) = r_b(t) p_{\text{req}}(t) \quad (5.17)$$

Table 5.1. Simulation, DRL, and Surrogate Model Hyperparameters

Parameter	Value
-----------	-------

Coordinator SAC: Policy/Critic architecture	3 layers, 256 neurons/layer
Bus agent SAC: Policy/Critic architecture	2 layers, 64 neurons/layer
SAC learning rate (coordinator/bus)	$3 \times 10^{-4} / 1 \times 10^{-3}$
SAC batch size (coordinator/bus)	256 / 256
SAC replay buffer (coordinator/bus)	500,000 / 200,000
SAC discount factor γ (coordinator/bus)	0.99 / 0.995
Target update coefficient τ	0.005
Episode length	900 s, 15 min at 1 Hz
Forecast surrogate: XGBoost	max_depth=4, learning_rate=0.08, subsample=0.8, n_estimators=300
Smoothness weights (λ_c, η)	$10^{-2}, 10^{-3}$
Envelope penalties (μ_{30}, μ_{120})	0.01, 0.02 kW ⁻¹
Bus dynamic models	1st/2nd order, $\omega_n = 0.109 \text{ rad/s}$, BESS/DW $\tau = 5 \text{ s}$
Buffer margin β (selected)	5%
Number of tap positions	20
Tap settings (min, max)	(0.766, 1.30) p.u.
Deadband v_{db}	0.01 p.u.
Smoothing horizon T_{lim}	30 s

For end-to-end system validation, three control strategies are compared:

- **Flex only:** The proposed hierarchical controller regulates voltage using only demand-side active-power flexibility, with OLTC tap positions fixed.
- **Tap only:** A conventional OLTC-based strategy regulates the same node using tap operations only, without active flexibility modulation.
- **Flex + Tap:** Combined strategy where the hierarchical controller and OLTC act simultaneously; flexible resources handle fast, local deviations while OLTC provides slower baseline correction.

5.3.2 Surrogate Flexibility Forecasting Performance

The accuracy of the XGBoost surrogate models is fundamental to the overall framework, as these forecasts determine the availability bounds used in both coordinator droop scaling and bus agent feasibility projection. Each bus agent maintains separate XGBoost models for HVAC, BESS, and dishwasher flexibility, trained on historical data and evaluated on a held-out validation day.

Table 5.2 presents the forecast performance for all three appliance types at Load Bus 5, comparing XGBoost against GRU and MLP baselines. For HVAC flexibility, XGBoost achieves the lowest RMSE (3.11 kW) and MAE (2.568 kW) with minimal bias (0.125 kW), outperforming both GRU (RMSE 3.735 kW) and MLP (RMSE 5.13 kW). For BESS flexibility, XGBoost similarly achieves the best performance (RMSE 0.375 kW, MAE 0.244 kW) with

negligible bias. For dishwashers, all models show higher relative errors due to the intermittent and stochastic nature of shiftable loads, but XGBoost remains competitive (RMSE 1.811 kW, MAE 1.076 kW).

Table 5.2. Surrogate Model Performance for Aggregated Flexibility Forecasts at Bus 5

Appliance	Surrogate Model	RMSE (kW)	MAE (kW)	BIAS (kW)
HVAC	GRU	3.735	3.325	-0.260
	Proposed XGB	3.110	2.568	0.125
	MLP	5.130	4.012	0.506
BESS	GRU	0.443	0.311	0.051
	Proposed XGB	0.375	0.244	-0.058
	MLP	0.603	0.480	-0.400
DW	GRU	1.738	1.088	0.337
	Proposed XGB	1.811	1.076	0.501
	MLP	1.841	1.134	0.494

These results justify the use of surrogate-derived caps $p_{\max}(t)$ in the droop computation (Equation 5.5) and the feasibility sets in the QP projection (Equation 5.15). The low bias and moderate RMSE ensure that the availability estimates are sufficiently accurate for real-time control, while the 5% buffer margin provides robustness against the remaining forecast errors.

5.3.3 Bus-Agent DRL Performance

The next stage of validation assesses the ability of each bus agent to translate allocated requests into feasible appliance-level setpoints while respecting device dynamics and grid response requirements. The bus agents are trained in simulation with the full IEEE 13-bus power flow and appliance dynamics, then evaluated on a validation day.

Table 5.3 compares the performance of the proposed SAC bus agent against TD3, DDPG, and PPO at Load Bus 5.

Table 5.3. Load Bus 5 DRL Agent Performance Comparison

DRL Model	NMAE	sMAPE	Energy Tracked (%)	Mean Reward
Proposed SAC	0.095	0.131	96.891	-0.070
TD3	0.142	0.209	114.065	-0.247
DDPG	0.241	0.289	124.065	-0.312
PPO	0.828	1.502	17.515	-0.773

The proposed SAC agent significantly outperforms all baselines across every metric. It achieves the lowest tracking error and delivers 96.89% of the target energy. Table 5.4 presents the performance of SAC bus agents at Load Buses 1 and 6. The results demonstrate consistent performance across the network, with NMAE values of 0.080 and 0.119, and energy tracking of 95.95% and 96.80%, respectively. This consistency

confirms that the SAC-based architecture generalizes well to different buses with varying load profiles and flexibility characteristics.

Table 5.4. SAC Bus Agent Performance Across Load Buses

DRL Agent	NMAE	sMAPE	Energy Tracked (%)	Mean Reward
Bus 1	0.080	0.151	95.950	-0.080
Bus 6	0.119	0.274	96.804	-0.104

Fig. 5.2 provides a visual assessment of tracking accuracy by plotting delivered flexibility against target flexibility for all three bus agents over the validation day. The points cluster tightly around the ideal $y = x$ reference line, confirming unbiased tracking across the full operating range. The slight spread at higher setpoints, particularly for Bus 6, reflects increased uncertainty near operational limits and aligns with the slightly higher NMAE and sMAPE values reported in Table 5.4.

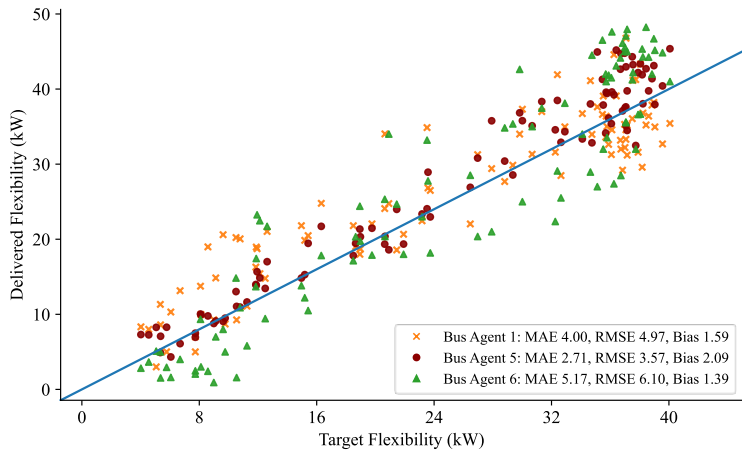


Figure 5.2. Delivered versus target flexibility on the validation day for all bus agents.

Figure 5.3 illustrates the stacked flexibility allocation per resource at each bus, revealing the dynamic interplay among HVAC, BESS, and dishwasher resources in achieving aggregate targets.

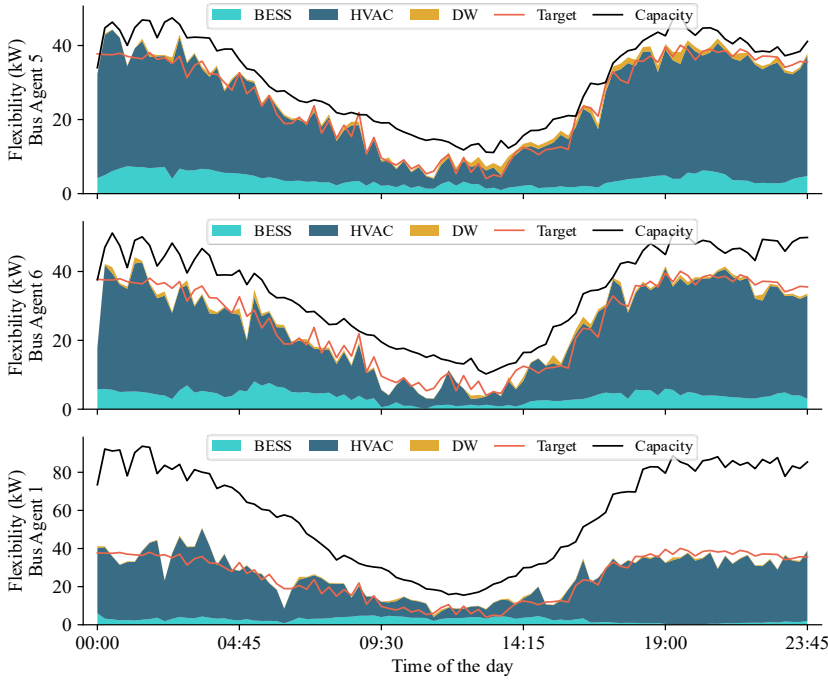


Figure 5.3. Flexibility allocations of SAC bus agents for BESS, HVAC, and DW, compared with bus-level targets and capacity envelopes.

HVAC systems deliver the dominant share of slowly varying flexibility, leveraging their thermal inertia for sustained modulation. BESS units absorb higher-frequency variations, providing a fast response to correct tracking errors. Dishwashers, with their discrete and intermittent availability, contribute occasional blocks of flexibility when active.

5.3.4 Coordinator Agent Performance

The coordinator agent must translate PCC voltage deviations into aggregate flexibility requests and allocate these requests across buses in a manner that maximizes voltage correction while respecting availability limits. To isolate and evaluate the coordinator's performance independent of bus-agent tracking errors, this validation uses synthetic request profiles generated from the droop-based voltage mapping, with bus agents assumed to track perfectly. The coordinator SAC policy is validated under four representative aggregate flexibility request profiles, including ramp, sag, swell, and noise, generated through the droop-based voltage mapping using the surrogate-derived $p_{max}(t)$.

Table 5.5 presents error metrics for each scenario, including MAE, RMSE, sMAPE, the percentage of samples within ± 1 kW and ± 5 kW of the target, and the saturation ratio (percentage of time the request hits the flexibility limits).

Table 5.5. Coordinator Agent Validation for Different Scenarios

Scenario	MAE (kW)	RMSE (kW)	sMAPE	% ≤ 1 kW	% ≤ 5 kW	Sat. ratio (%)
Flat	0	0	0	100	100	0
Noise	1.134	1.431	1.128	53	100	0
Ramp	4.334	5.584	0.139	23.67	58.67	79.92
Sag step	1.477	5.956	0.441	91.33	93.25	2.25
Swell step	0.935	4.066	0.426	92.67	94.67	1.17

In the ramp scenario, errors increase because the synthetic request pushes the controller to its flexibility limits; about 80% of samples operate at saturation, demonstrating that the agent correctly exploits the full envelope without destabilizing the system. In the noise scenario, the coordinator effectively filters out unreasonably fast fluctuations, never saturates, and maintains all samples within ± 5 kW, which is essential when operating on noisy voltage measurements. For the sag and swell step scenarios, the coordinator achieves excellent tracking, with more than 91% of samples within ± 1 kW and over 93% within ± 5 kW. The low saturation ratios (2.25% and 1.17%) indicate that the agent responds quickly to step changes without excessive overshoot.

Fig. 5.4 visualizes the coordinator's response under all four scenarios; plotting delivered versus requested flexibility. The plots confirm the quantitative findings: near-perfect tracking for flat and step responses, effective noise filtering, and correct saturation behavior during the ramp.

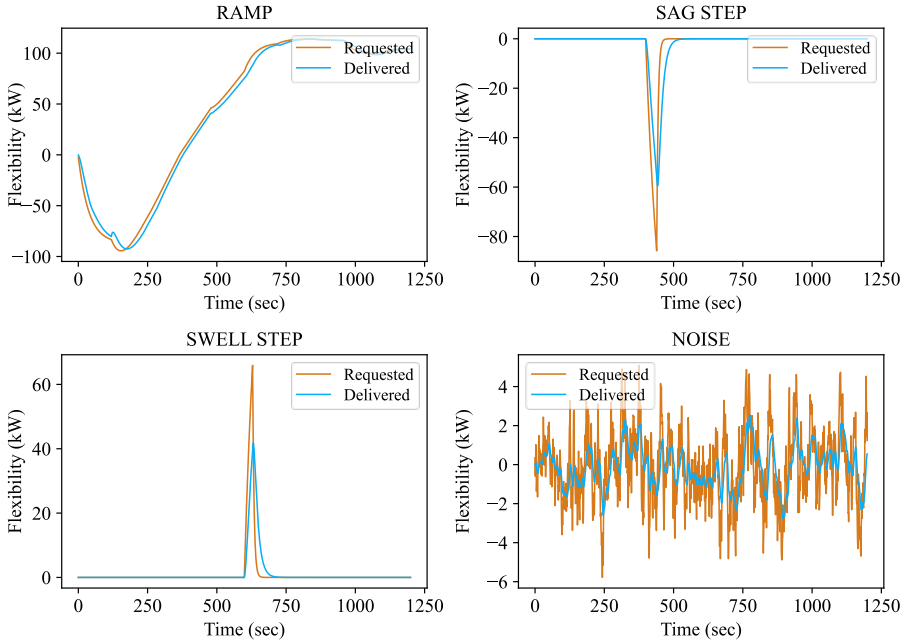


Figure 5.4. Coordinator agent response under ramp, sag, swell, and noise scenarios, showing delivered versus requested flexibility.

To quantify the benefit of learning context-aware allocations, the SAC coordinator is

compared against a fixed capacity-proportional allocation baseline (Equation 5.17). Both strategies are evaluated in closed-loop simulation with the same bus agents and disturbance profiles. Table 5.6 presents the resulting voltage quality metrics at the PCC.

Table 5.6. Comparison of Learned SAC Allocation vs. Capacity-Proportional Allocation

Configuration	% within ± 10 V	% within ± 15 V
SAC-learned allocation	88.54	98.65
Fixed allocation (capacity-proportional)	81.27	92.40

The learned policy implicitly captures the operating-point-dependent relationship between bus-level injections and PCC voltage, a capability that would otherwise require an explicit network model.

5.3.5 Hardware-in-the-Loop (HIL) Validation on RTDS

The complete hierarchical framework, including SAC coordinator, three SAC bus agents, XGBoost surrogates, and QP feasibility layers, is integrated with the RTDS-simulated IEEE 13-bus system for closed-loop validation. Three control strategies are compared in the HIL experiments:

- **Flex only:** The proposed hierarchical controller regulates voltage using only active-power flexibility, with OLTC tap positions fixed.
- **Tap only:** A conventional OLTC-based strategy regulates the same node using tap operations only, without active flexibility modulation.
- **Flex + Tap:** Combined strategy where the hierarchical controller and OLTC act simultaneously; flexible resources handle fast, local deviations while OLTC provides slower baseline correction.

Table 5.7 summarizes the voltage statistics and OLTC operations for each strategy.

Table 5.7. Voltage Statistics and OLTC Operations for different operating modes

Case	V_min (V)	V_max (V)	V_mean (V)	% within ± 10 V	% within ± 15 V	Tap Count
Flex only	383.64	421.67	396.60	68.68	91.82	0
Tap only	383.51	428.56	403.91	86.18	96.18	26
Flex+Tap	389.27	424.70	403.43	88.54	98.65	7

In the Flex-only case, the controller maintains voltage within ± 15 V for 91.82% of the simulation time and within ± 10 V for 68.68% of the time, without any tap operations. The remaining excursions occur primarily during periods of extreme disturbance when available flexibility is insufficient.

The Tap-only case improves ± 10 V compliance to 86.18% and ± 15 V compliance to 96.18%, but at the cost of 26 tap operations and a higher maximum overvoltage (428.56 V). This reflects the classical trade-off between voltage regulation and mechanical wear, as well as the coarser granularity and slower response of tap changes.

The combined Flex+Tap strategy achieves the best overall performance: 88.54% of samples within ± 10 V, 98.65% within ± 15 V, and only 7 tap operations, a 73% reduction

compared to Tap-only. The standard deviation of voltage is also lowest (5.29 V), indicating smoother regulation. Flexible loads absorb rapid, small deviations, while OLTC adjustments are reserved for slower, structural changes in power flow.

Fig. 5.5 depicts representative voltage trajectories for all three strategies over a 2000-second window. The Flex+Tap trajectory shows significantly suppressed deep sags and sharp swells compared to Tap-only, while the Flex-only trajectory exhibits larger excursions during extreme events.

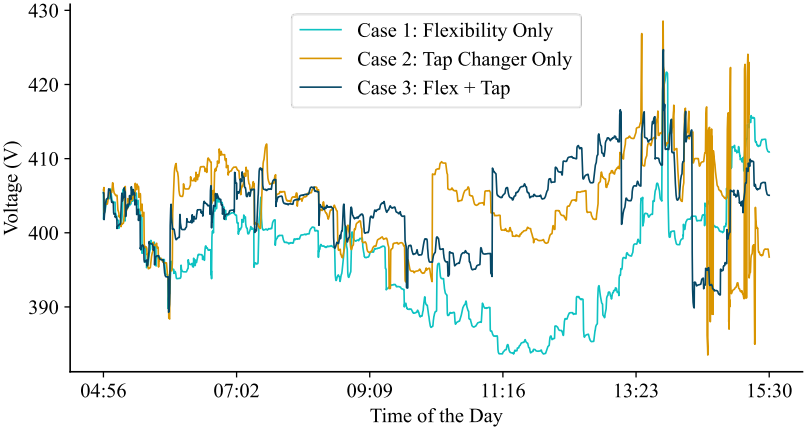


Figure 5.5. RTDS voltage trajectories for Flex only, Tap only, and Flex+Tap strategies, demonstrating superior performance of combined control.

Table 5.8 evaluates the accuracy of flexibility service delivery in the RTDS experiments by comparing requested and delivered peak flexibility. In the Flex-only case, the delivered peak (131.66 kW) closely matches the requested peak (132.44 kW), with MAE of 3.77 kW and RMSE of 5.20 kW, corresponding to normalized errors of 2.85% and 3.93% of the peak, respectively. For Flex+Tap, the controller delivers a slightly reduced peak, reflecting the more constrained operating envelope when coordinating with OLTC actions.

Table 5.8. Flexibility Service Provision on RTDS for Flex Only and Flex+Tap Scenarios

Case	Req_peak (kW)	Delivered_peak (kW)	MAE (kW)	RMSE (kW)	Up MAE (kW)	Down MAE (kW)
Flex only	132.44	131.66	3.77	5.20	4.11	3.60
Flex+Tap	76.10	71.79	3.99	5.77	3.87	4.32

Figure 5.6 provides a detailed view of an interval from the Flex+Tap experiment, illustrating the real-time flexibility allocations from Bus Agents 1, 5, and 6, and the corresponding voltage trajectory at the target bus. The stacked area plot shows how each bus contributes to the total delivered flexibility, with HVAC providing the base load modulation, BESS responding to fast transients, and dishwashers contributing occasional blocks. The voltage trajectory at the bottom confirms that this coordinated response successfully maintains voltage within the target band throughout the interval.

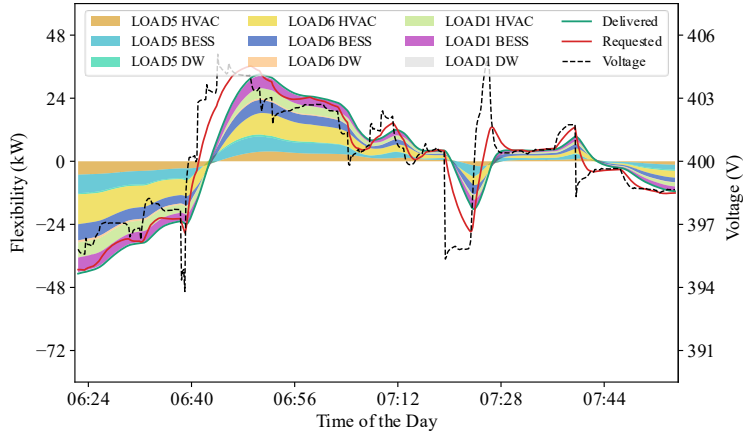


Figure 5.6. Real-time flexibility allocations from Bus Agents 1, 5, and 6, and the corresponding voltage trajectory at the target bus during Flex+Tap operation.

5.3.6 Stress Testing and Sensitivity Analysis

To assess robustness beyond the baseline conditions, the controller is evaluated under five stress scenarios executed in the same RTDS setup over the identical evaluation window and disturbance timeline, with only the stressor changed: doubled PV generation, doubled wind generation, halved demand, random unavailability of 50% of HVAC resources, and $\pm 20\%$ multiplicative error injected into the surrogate flexibility forecasts. Fig. 10 compares $\pm 10\text{V}$ voltage compliance and OLTC operations across all scenarios for the three control strategies. The combined Flex + Tap strategy retains the highest compliance in every scenario (81.3–90.1%), with a maximum degradation of 7.2 percentage points under 50% HVAC unavailability, consistent with HVAC providing the dominant flexibility share (Fig. 6), and reduces tap operations by 67–73% relative to tap-only control in all cases. Flexibility tracking degrades (nMAE between 0.071 and 0.156 across scenarios), with the forecast-error case corroborating the buffer-margin selection of $\beta = 5\%$.

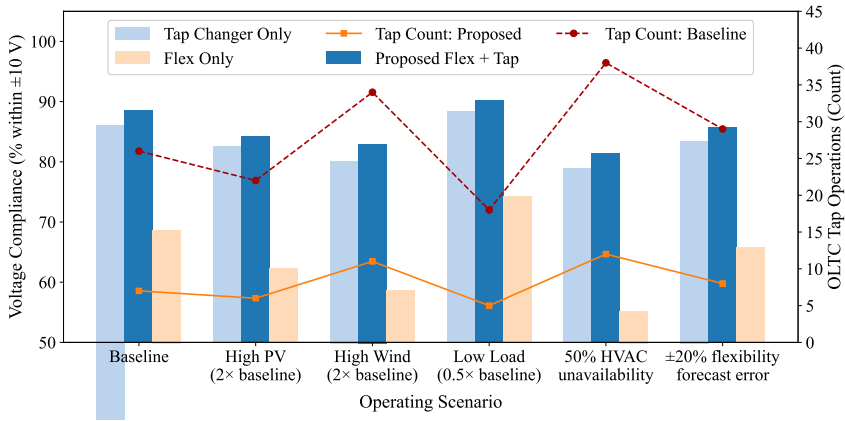


Figure 5.7. Voltage compliance ($\pm 10\text{V}$) and OLTC tap operations under different scenarios.

5.4 Summary

This chapter has presented a hierarchical, model-free framework for real-time voltage regulation in active distribution networks using only active-power residential flexibility. The proposed architecture combines a SAC-based coordinator that learns implicit voltage–power sensitivities from interaction data, with distributed SAC bus agents that translate allocated requests into feasible appliance-level setpoints through XGBoost-based forecasting and quadratic programming projection. The framework operates without any knowledge of network topology or line parameters, relying solely on a single-point voltage measurement at the point of common coupling.

Validation on an RTDS-based IEEE 13-bus system with real weather-driven disturbances demonstrated that the framework achieves 88.5% voltage compliance within ± 10 V and reduces OLTC operations by up to 73% compared to tap-only control, while maintaining 96.9% flexibility-tracking accuracy. On an annual basis, this translates to 6,935 fewer OLTC operations. Since OLTC maintenance is typically required after 50,000–100,000 operations, such a reduction significantly extends maintenance intervals and yields OPEX savings. Furthermore, the learned coordinator agent allocation improved tight voltage compliance by 7.3% points over fixed capacity-proportional allocation, confirming that the SAC policy successfully captures operating-point-dependent voltage sensitivities.

These results establish that low-observability, model-free voltage regulation using aggregated demand-side flexibility is feasible for practical distribution feeders, complementing the frequency regulation capabilities developed in Chapter 4.

6 Conclusion

The transition to a decarbonized power system has long been framed as a supply-side challenge, yet the most profound operational shift may well occur at the network's edge, where millions of small, heterogeneous, and behaviorally complex resources must be orchestrated as reliable grid infrastructure. This thesis has addressed the central unresolved challenge of transforming residential demand-side flexibility into a scalable, market-compliant resource capable of delivering both system-level frequency services and distribution-level voltage support. The core finding is that residential flexibility becomes operationally valuable only when it is coherently structured across its full lifecycle—from behavioral characterization and dynamic capability mapping to risk-aware market participation and real-time delivery. By embedding appliance dynamics, user comfort constraints, and uncertainty into a unified framework, the thesis demonstrates that residential portfolios can transition from theoretical potential to verifiable, high-performance grid services.

The original contribution of this work lies in the development and validation of an end-to-end, data-driven operational architecture:

- Its foundation is a flexibility quantification engine that learns comfort boundaries directly from consumer behavior, mapping shiftable, thermostatic, and storage resources into symmetrical reserve envelopes without static assumptions.
- A transfer-learning-based multi-input multi-feature neural network overcomes the data-scarcity barrier facing new aggregators, delivering accurate community-level forecasts while requiring telemetry from as few as 17% of households.
- The translation of these steady-state forecasts into dynamically deliverable bids is achieved through a novel capability-mapping mechanism that enforces physical ramp-rate constraints via a mixed-integer linear programming formulation, ensuring that commitments respect fast frequency service activation timelines.
- A risk-aware hierarchical disaggregation strategy then allocates commitments to individual devices using availability-weighted quantiles and CVaR-lite, systematically reducing fleet-level under-delivery risk by 31–48 % compared with conventional proportional methods.
- Real-time compliance is maintained through fast optimization and battery-compensated droop tracking, achieving coverage ratios exceeding unity and mean absolute tracking errors within market tolerance.
- The integrated BRP-aggregator economic optimization further reveals that this technical capability translates into genuine value creation, achieving net operational cost reductions of 4.75% despite the inherent trade-offs between frequency-driven activations and residual imbalance exposure.

Beyond balancing markets, the thesis establishes that the same aggregated flexibility can serve as a fast voltage support actuator without requiring explicit grid models, a capability of profound importance for distribution system operators facing high distributed energy resource penetration. The hierarchical multi-agent deep reinforcement learning framework, operating under centralized training with distributed execution, learns implicit voltage-power sensitivities through interaction rather than

calculation, enabling real-time voltage regulation that reduces on-load tap changer operations by up to 73% while maintaining statutory voltage compliance. The surrogate-embedded feasibility projection, integrating XGBoost forecasting with bounded-simplex quadratic programming, ensures that all control actions are physically realizable, a critical innovation that distinguishes this approach from unconstrained reinforcement learning strategies that risk generating infeasible setpoints.

The synthesis of results demonstrates that residential flexibility, when properly quantified and coordinated, can meet the dual objectives of reliability and economic viability. The work shows that uncertainty stemming from human behavior, device dynamics, and limited data can be systematically managed through learning-based forecasting and risk-aware allocation. The demonstrated ability to coordinate slower thermal loads with fast-responding storage resources highlights the importance of multi-vector coordination in achieving both endurance and responsiveness. In doing so, the thesis reframes residential demand not as a passive or stochastic element, but as an actively controllable, learning-enabled grid participant whose comfort constraints become operational parameters rather than insurmountable barriers.

The broader implications of this work extend across research, policy, and industry:

- For the scientific field, the thesis provides a unified framework that bridges the long-standing fragmentation between flexibility characterization, market integration, and real-time control, offering a foundation for future work on scalable, AI-enabled energy systems.
- For policy and regulation, the findings support the feasibility of deeper residential participation in ancillary service markets, reinforcing the objectives of the EU Clean Energy Package by demonstrating that small-scale resources can meet technical and economic requirements when properly aggregated and coordinated.
- For industry stakeholders, including aggregators, TSOs, and DSOs, the research delivers deployable methodologies that reduce operational risk, enable new revenue streams, and defer infrastructure investment through software-defined flexibility solutions. In particular, the demonstrated reduction in reliance on mechanical voltage control and the ability to provide fast frequency response from distributed assets point toward a more decentralized and resilient grid architecture.

In conclusion, this thesis establishes that the true value of residential demand-side flexibility lies not in its individual components, but in its systemic integration. By unifying data-driven modeling, market-oriented optimization, and real-time control within a single operational pipeline, the research advances both the theory and practice of flexibility utilization. It provides compelling evidence that residential energy systems, when intelligently coordinated, can play a decisive role in addressing the dual challenges of decarbonization and grid stability.

7 Future Work

The research presented in this thesis establishes comprehensive frameworks for quantifying, aggregating, and coordinating residential demand-side flexibility to provide frequency regulation and voltage control services. While the results demonstrate significant advancements in enabling residential aggregators to participate in ancillary service markets, several promising directions for future investigation emerge from the limitations of the current work.

A natural extension involves adapting the proposed frameworks to asymmetric reserve products such as FCR-D, aFRR, and mFRR, each imposing distinct activation timelines and duration requirements. A further direction is the development of multi-timescale optimization frameworks that allow the same portfolio of flexible resources to simultaneously contribute to multiple markets for provision of both frequency and voltage services, requiring sophisticated co-optimization.

The flexibility resources considered could be expanded to include electric vehicles with mobility patterns requiring probabilistic availability modelling, and heat pumps integrated with thermal storage offering longer time constants suitable for extended-duration services. Critical investigation is also needed into coordinated provision of TSO-level frequency regulation and DSO-level voltage control, which are treated separately but are inherently interdependent.

Methodological enhancements should explore end-to-end learning that jointly optimizes forecasting and control, online adaptation mechanisms that maintain performance as device characteristics drift, and more systematic uncertainty quantification through probabilistic forecasting and distributionally robust optimization to improve reliability while reducing conservatism. Real-world pilot demonstrations are essential to validate these frameworks under actual operational conditions, where communication latency, metering inaccuracies, and regulatory compliance introduce challenges not fully captured in simulation.

Comprehensive economic analysis must assess the viability of residential aggregation under current and projected market conditions, considering multiple revenue streams, technology costs, and customer retention. The operational frameworks developed here could also inform long-term grid planning by providing realistic estimates of the flexibility that residential communities can reliably deliver, potentially enabling DSOs to defer network reinforcements through flexibility services.

In conclusion, this thesis has established methodological foundations for enabling residential demand-side flexibility to provide essential grid services. The future research directions outlined chart a path toward practical, scalable deployment, addressing the technical, economic, and regulatory challenges that stand between demonstrated feasibility and widespread adoption in transitioning power systems.

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Abstract

This doctoral thesis addresses the aggregation and coordination of residential demand-side flexibility for electricity balancing market participation and voltage regulation in active distribution networks. It is motivated by the growth of renewable generation, electric vehicles, heat pumps, battery storage, and other distributed energy resources, which increase operational variability and reduce the contribution of conventional generation to frequency and voltage stability. Yet residential flexibility remains fragmented, behaviour-dependent, and constrained by appliance dynamics, comfort requirements, and limited observability.

The thesis develops and validates an integrated framework that enables residential flexibility to be quantified, forecasted, aggregated, converted into market-compliant reserve bids, and coordinated in real time. The framework combines data-driven flexibility assessment, artificial-intelligence-based forecasting, optimization, and real-time control in one operational chain. It focuses on thermostatically controlled loads, shiftable household appliances, and battery energy storage systems, while ensuring that flexibility activation remains compatible with user comfort.

A method learns user comfort boundaries from consumer behaviour to define feasible operating regions, forming symmetrical reserve-capacity envelopes for frequency regulation services. At the community level, a transfer-learning-based multi-input, multi-feature neural network forecasts flexibility when historical measurement data are available only for a limited share of households. The forecasted flexibility is then transformed through aggregator-side optimization into market-compliant FCR-N reserve bids and allocated to households and devices using a risk-aware strategy that reduces under-delivery risk and limits user discomfort. In this context, reserve refers to the committed symmetrical active-power capacity, while frequency response refers to the real-time delivery of this committed capacity during activation.

Beyond balancing market participation, the thesis studies voltage regulation in active distribution networks as a distribution-level application of residential flexibility. A model-free deep reinforcement learning framework is proposed that does not require detailed grid parameters or network topology. Instead, it learns the relationship between voltage deviations and active-power flexibility from measurement data, enabling aggregated demand-side flexibility to maintain voltages within statutory limits and reduce reliance on mechanical voltage-regulation devices (OLTCs) in tested conditions.

The results show that, when properly quantified, forecasted, aggregated, and coordinated, residential flexibility can operate as a reliable grid-support resource. Real-time digital simulator experiments confirm that the proposed framework can support frequency-response delivery for FCR-N reserve provision, improve voltage quality, reduce mechanical voltage-control actions, and create economic value for aggregators and balance responsible parties. The main scientific contribution of the thesis lies in linking flexibility quantification, forecasting, market participation, risk-aware disaggregation, real-time coordination, and voltage regulation into a unified system-level framework.

The findings demonstrate that residential consumers can become active flexibility-service providers in future power systems. Through artificial intelligence, data-driven

control, and aggregation, residential flexibility can support higher renewable energy integration, strengthen system reliability, and contribute to a more flexible, decentralized, and climate-neutral energy system.

Keywords: demand-side flexibility, aggregation, balancing market, frequency regulation, active distribution network, voltage regulation, artificial intelligence, deep reinforcement learning.

Lühikokkuvõte

Käesolev doktoritöö käsitleb seda, kuidas kodumajapidamistes peituvat elektritarbimise paindlikkust saab koondada ja juhtida nii elektrisüsteemi tasakaalustamise kui ka jaotusvõrgu pingereguleerimise eesmärgil. Teema olulisus kasvab koos taastuvenergia, elektrisõidukite, soojuspumpade, akusalvestite ja teiste hajutatud energiaressursside kiire levikuga. Need arengud muudavad elektrisüsteemi töö muutlikumaks sh sageduse ja pingestabiilsuse tagamisel. Samal ajal on kodutarbijate paindlikkus seni olnud killustunud ja keerukalt kasutatav, sest see sõltub tarbijate harjumustest, seadmete tööpõhimõtetest, mugavusootustest ning piiratud mõõteandmetest.

Doktoritöös töötatakse välja ja valideeritakse integreeritud raamistik, mis võimaldab kodumajapidamiste paindlikkust hinnata, prognoosida, koondada, vormistada turureeglitele vastavateks reservipakkumisteks ning juhtida reaajas. Raamistik ühendab andmepõhise paindlikkuse hindamise, tehisintellektil põhineva prognoosimise, optimeerimise ja reaajas juhtimise üheks tervikuks. Uurimus keskendub eelkõige termostaatilistelt juhitavatele koormustele, ajaliselt nihutatavatele kodumasinadele ja akusalvestitele, arvestades samal ajal vajadust säilitada tarbijate mugavus.

Töös pakutakse välja meetod, mis õpib tarbijakäitumise põhjal kasutajate mugavuspiire ning määrab nende alusel seadmete lubatud töövahemikud. See võimaldab hinnata, millises ulatuses saab kodumajapidamiste tarbimist kasutada sageduse reguleerimise teenuste pakkumiseks. Kogukonna tasandil kasutatakse ülekandeõppel põhinevat mitme sisendi ja mitme tunnusega närvivõrku, et prognoosida paindlikkust ka olukorras, kus ajaloolised mõõteandmed on olemas vaid väikese osa majapidamiste kohta. Prognoositud paindlikkus teisendatakse agregatori optimeerimismudeli abil FCR-N reserviturule sobivateks pakkumisteks ning jaotatakse seejärel majapidamiste ja seadmete vahel riskiteadlikult, vähendades nii alatäitmise ohtu kui ka tarbijatele põhjustatavat ebamugavust. Selles kontekstis tähendab reserv kohustatud sümmeetrilist aktiivvõimsuse võimekust, samas kui sagedusvastus tähendab selle kohustatud võimekuse reaajas osutamist aktiveerimise ajal.

Lisaks tasakaalustamisturul osalemisele uuritakse doktoritöös kodumajapidamiste paindlikkuse kasutamist jaotusvõrgu pingereguleerimiseks. Selleks pakutakse välja mudelivaba sügava stiimulõppe raamistik, mis ei eelda detailseid teadmisi võrgu parameetrite ega topoloogia kohta. Raamistik õpib mõõteandmete põhjal seoseid pinget kõrvaldale ja aktiivvõimsuse paindlikkuse vahel ning võimaldab koondatud tarbimispoole paindlikkust kasutada pingete hoidmiseks lubatud piirides. Katsetulemused näitavad, et selline lähenemine võib vähendada vajadust mehaaniliste pingereguleerimiseseadmete, näiteks koormuse all reguleeritavate astmelülite (OLTC), kasutamise järele.

Tulemused kinnitavad, et kodumajapidamiste paindlikkus võib nõuetekohase hindamise, prognoosimise, koondamise ja juhtimise korral toimida usaldusväärse elektrisüsteemi toetava ressursina. Reaalajasimulaatoriga RTDS tehtud katsed näitavad, et väljapakutud raamistik toetab FCR-N reservi jaoks vajalikku sagedusvastust, parandab pingekvaliteeti, vähendab mehaaniliste pingereguleerimistoimingute arvu ning loob majanduslikku väärtust nii agregatoritele kui ka bilansihalduritele. Doktoritöö peamine teaduslik panus seisneb selles, et paindlikkuse hindamine, prognoosimine, turuosalus, riskiteadlik

jaotamine, reaalajas koordineerimine ja pinge reguleerimine seotakse ühtseks süsteemitasandi raamistikuks.

Töö tulemused näitavad, et kodutarbijatest võivad tuleviku elektrisüsteemides saada aktiivsed paindlikkusteenuste pakkujad. Tehisintellekti, andmepõhise juhtimise ja agregeerimise abil saab kodumajapidamiste paindlikkus aidata suurendada taastuvenergia osakaalu, tugevdada elektrisüsteemi töökindlust ning toetada paindlikuma, hajutatuma ja kliimaneutraalsema energiasüsteemi kujunemist.

Märksõnad: tarbimispoole paindlikkus, agregeerimine, tasakaalustamisturg, sageduse reguleerimine, aktiivne jaotusvõrk, pinge reguleerimine, tehisintellekt, sügav stiimulõpe.

Appendix 1

Publication I

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Leveraging the machine learning techniques for demand-side flexibility – A comprehensive review

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ABSTRACT

The increasing reliance on renewable energy sources poses challenges in managing the grid, necessitating a focus on energy efficiency and grid stability for a smooth energy transition. Demand-side flexibility is a key element in improving grid reliability. Conventional flexibility methods, like demand response and load shifting, are limited by the complexities of learning consumer behavior, managing the variability of energy resources, and making near real-time decisions. Artificial intelligence (AI) provides an effective solution to these challenges by addressing non-linear appliance scheduling problems, predicting flexible loads, and implementing learning-based control strategies. This review examines the applications of AI in demand-side flexibility by analyzing flexibility characterization, quantification, optimization, and forecasting. A thorough analysis is conducted on AI techniques, breaking them down into their fundamental metrics and methods for various flexibility applications. Based on this foundation, the AI Flexibility Performance Framework (AFPF) is developed to establish a standardized mechanism for comparing the effectiveness of different AI-accelerated flexibility techniques. This framework includes the Business-to-Consumer (B2C) Flexibility Index and the Consumer Relevance Indicator, employing a binary scoring mechanism to guide future research toward balancing technological advancements with consumer-centric approaches.

1. Introduction

The energy system is rapidly shifting towards sustainable and renewable alternatives, such as wind and photovoltaics. However, this transition brings complexity due to the inherent variability and intermittency of renewable energy, which introduces reliability challenges in grid management [1]. To address these issues, innovative technologies are being implemented to stabilize the grid and optimize energy distribution. Demand-side management gains importance in this context by helping to manage grid operations, reduce peak demand, enhance energy efficiency, and facilitate the integration of distributed energy resources into the power system [2]. In this context, smart grids allow consumers to monitor and manage their electricity usage in real-time, allowing for adaptive response to grid conditions [3]. Buildings

account for 35 % of global energy consumption and are key contributors to the smart grid. Energy flexibility in buildings enables adjustments in energy consumption by end-users in response to signals from grid operators, often in exchange for financial incentives. This potential for energy flexibility in buildings is of significant interest to aggregators, building managers, and end-users [4].

Demand-side flexibility primarily involves consumers actively participating in the energy market by adjusting their electricity demand in real-time through demand response [5]. This adjustment balances energy supply and demand in quantity and time, extending beyond load reduction or appliance shifting [6]. Therefore, demand-side flexibility is defined as the ability of power system assets and consumers to adapt operations temporarily in response to external service requests without causing unplanned disruptions [7]. Fig. 1 shows various strategies and

Abbreviations: AI, Artificial Intelligence; ANN, Artificial Neural Network; CNN, Convolutional Neural Network; DER, Distributed Energy Resources; DHW, Domestic Hot Water; DR, Demand Response; EV, Electric Vehicle; XG-Boost, Extreme Gradient Boosting; HVAC, Heating, Ventilation, and Air Conditioning; KNN, K-Nearest Neighbour; LSTM, Long Short-Term Memory; ML, Machine Learning; MAE, Mean Absolute Error; NSGA, Non-dominated Sorting Genetic Algorithm; PCA, Principal Component Analysis; PSO, Particle Swarm Optimization; RL, Reinforcement Learning; RMSE, Root Mean Square Error; SVM, Support Vector Machine.

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sources of demand-side flexibility.

Quantifying demand-side flexibility involves identifying the flexibility of each load, which is challenging due to the need for high-resolution appliance-level energy consumption data. Non-intrusive load monitoring techniques address this issue by identifying the operation of flexible appliances using aggregated electricity consumption data [8]. Artificial Intelligence (AI) is a popular tool for quantifying flexibility as it can analyze large amounts of data, identify patterns, and make predictions [9]. These individual flexibilities are combined through flexibility aggregation to create a single, aggregated resource to provide grid services and support renewable energy integration [10]. Balancing and ancillary services markets provide a regulatory medium for the transaction of flexibility services, thereby promoting cost-effective and eco-friendly options to balance the electric grid through load shifting, curtailment, and ancillary services [11]. Fig. 2 illustrates the structure of demand-side flexibility within the power system, incorporating distributed resources and market integration.

This review highlights the applications of AI techniques for demand-side flexibility and their suitability for practical implementation in the following manner:

- Conducting a detailed review of various aspects of flexibility, such as characterization, optimization, and forecasting, to highlight advancements and opportunities in smart energy management.
- Analysis of key elements of AI for demand-side flexibility, including objective function, training models, flexible assets, and performance metrics, offering critical insights for future research and application.
- Introducing an evaluation framework for the practical implementation of AI-accelerated flexibility techniques, considering consumer and market perspectives.

This study utilizes a detailed methodology that uses Scopus and Google Scholar as primary sources to identify relevant research articles. To search more specifically, logical operators such as "AND" and "OR" are used in queries. The asterisk symbol (*) also includes variations of a particular keyword, expanding the search scope. Table 1 presents some search queries used during the literature search phase.

The rest of the paper is organized as follows: Section 2 presents an overview of AI techniques and highlights their application in demand-side flexibility. Section 3 categorizes the reviewed articles according to different aspects of demand-side flexibility. In Section 4, the assessment framework is discussed, and key findings and implications derived from the study are summarized. Finally, Section 5 concludes the paper and identifies potential directions for future research.

2. Application of ai techniques in demand-side flexibility

Artificial intelligence enables machines to solve problems by identifying and selecting relevant information [12]. Its capability to quickly and accurately analyze extensive datasets makes it useful for numerous applications, including demand-side management [13]. AI uses predictive models to forecast renewable energy availability and electricity prices, minimizing overall system operational costs [14]. It also plays a significant role in smart grid technology, facilitating decision-making by directing energy to grid areas where it is most required or automatically adjusting the output of renewable energy sources to match fluctuations in demand [15]. Additionally, AI provides market-based mechanisms for energy consumers and producers to trade energy-related products and services in energy markets, allowing energy consumption or production adjustments based on renewable energy availability or price variations [16].

Integrating AI into demand-side flexibility enhances grid reliability by pooling diverse energy assets, such as electric vehicles and battery storage [17]. In flexibility markets, AI algorithms assist flexibility aggregators in predicting and optimizing energy demand and managing the market participation of numerous assets [18]. For instance, AI algorithms forecast the energy utilization of an electric vehicle fleet and optimize their charging and discharging schedules for profitable market engagement [19]. Furthermore, AI contributes to the development of nearly zero-energy buildings and optimizes HVAC systems to minimize grid reliance, using predictive algorithms for renewable energy availability and consumption forecasting [20–22]. It adjusts building heating and cooling based on predicted consumer occupancy patterns to enhance user comfort and energy efficiency [23]. Through user behavior analysis, AI regulates individual appliances, lighting systems, and energy consumption of other devices within buildings and evaluates cost-effective retrofitting measures [24–26].

2.1. Fundamentals of machine learning in demand-side flexibility

Machine learning utilizes supervised, unsupervised, deep, and reinforcement learning models to improve algorithm performance [27]. Key ML terminologies include model training, testing, underfitting, overfitting, bias, variance, regularization, cross-validation, and hyperparameter tuning [28]. Model training optimizes the parameters of a model based on input and output data [29]. Testing involves assessing the performance of a model on unseen data to guard against overfitting or underfitting [30]. Underfitting and overfitting refer to the inadequacy or overcomplexity of a model fit to data patterns [31,32]. Bias is the difference between the average prediction of a model and the actual

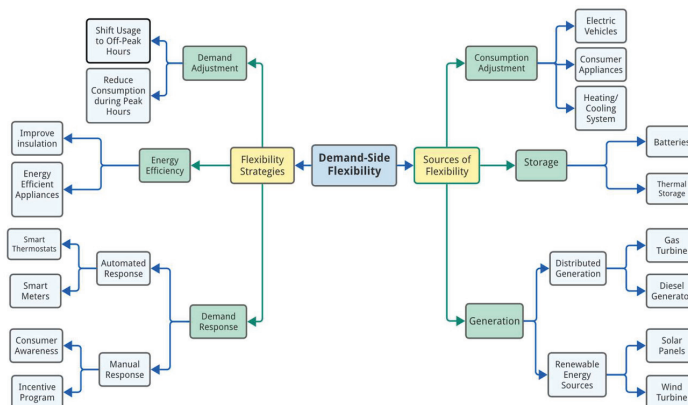


Fig. 1. Demand-side flexibility framework.

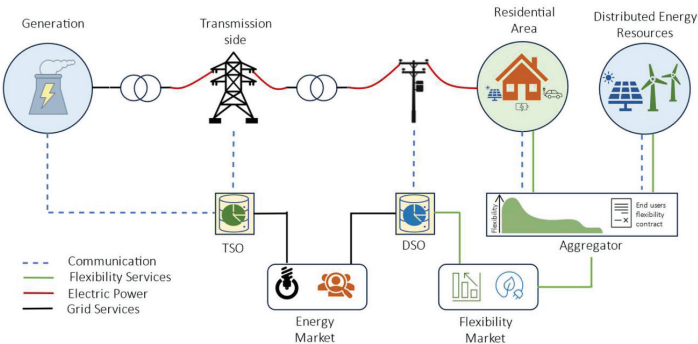


Fig. 2. Demand-side flexibility interaction with energy markets for grid services.

Table 1
Search queries for article selection.

Search Strings	Meaning
"AI" OR "machine learning" AND "demand-side flexibility"	Returns articles that mention AI or ML along with demand-side flexibility.
"Machine learning" AND "quantification" OR "characterization"	Returns articles that mention ML and either Quantification or Characterization.
"Data-driven" AND "energy flexibility"	Set the keywords related to data-driven and energy flexibility
"AI" OR "machine learning" AND "energy optimization"	Returns articles that mention AI or machine learning along with energy flexibility
"Machine Learning" OR "flexibility forecasting"	Set the keywords related to ML and flexibility forecasting

value, while variance predicts model variability across different training datasets [33]. Regularization, used to prevent overfitting, penalizes the cost function to discourage large parameter values [34].

ML models are evaluated using statistical metrics such as the coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), normalized mean bias error (NMBE), normalized root means square error (NRMSE), and coefficient of variation or root mean square error (CV-RMSE). According to the ASHRAE Guidelines [35], models with an NMBE of <10 % and a CV-RMSE of <30 % for hourly data predictions are considered acceptable accuracy levels.

2.1.1. Supervised learning

Supervised learning uses labeled datasets to train models by creating a functional mapping for accurate predictions of unseen data [36]. The two primary types of supervised learning are regression and classification. During training, the internal parameters of a model are adjusted using labeled input-output pairs to best fit the data [37]. Table 2 highlights studies that use supervised learning to analyze demand-side flexibility.

2.1.2. Unsupervised and reinforcement learning

In unsupervised learning, algorithms learn from unlabeled data by identifying inherent structures and patterns. It uses techniques like clustering to group similar data points and employs methods such as principal component analysis (PCA) for dimensionality reduction, simplifying datasets by decreasing variables [57]. Reinforcement learning (RL) involves agent interaction with an environment to learn optimal actions through rewards and penalties. The agent learns over time through trial and error, with each action resulting in a new state and corresponding reward or penalty [58]. Table 3 includes studies implementing unsupervised and RL for demand-side flexibility.

2.1.3. Deep learning

Deep learning uses multi-layered neural networks to interpret complex data by processing input data, computing hidden layers, and making predictions or classifications in the output layer. This functionality relies on the iterative refinement of weights and biases, guided by backpropagation and gradient descent [91]. Traditional deep learning models, such as long short-term memory (LSTM) networks [92], convolutional neural networks (CNNs) [93], and deep neural networks (DNNs) [79], have been increasingly applied in various domains of demand-side flexibility such as load forecasting, energy optimization, and demand response management.

These traditional deep learning models are enhanced by attention mechanisms and transformer architectures, which are designed to handle sequential data and improve model performance in capturing long-range dependencies. The attention mechanism enables models to focus on specific parts of the input data that are more relevant to the task at hand by assigning different weights to different input elements. This allows the model to concentrate on the most critical parts of the data. On the other hand, transformer models such as GPT, process entire sequences in parallel by utilizing self-attention mechanisms rather than sequentially, as in the case of LSTM networks. This not only improves the efficiency and scalability of models but also enhances their ability to capture complex relationships within data [80]. For instance, temporal fusion transformer (TFT) combines LSTM networks with attention mechanisms to identify significant temporal patterns, thereby improving the accuracy of energy demand forecasting, even in contexts where historical data is limited [81]. To incorporate physical laws into the learning process, physics-informed neural networks (PINN) have gained attention for their ability thereby enhancing the model's generalization capabilities in energy-related applications [82]. Table 4 shows the application of deep learning in demand-side flexibility.

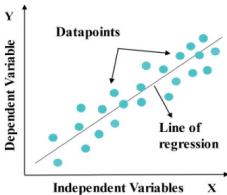
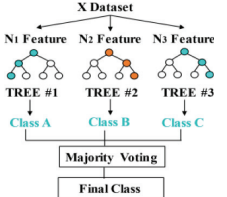
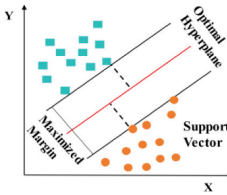
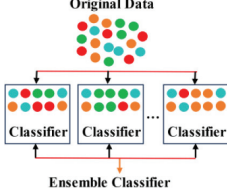
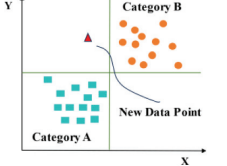
3. Demand-side flexibility aspects in AI-Enabled environments

Exploring AI-driven demand-side flexibility involves optimizing and managing energy consumption patterns based on real-time data and predictive analytics [114]. While flexibility optimization enhances energy efficiency, flexibility characterization categorizes the flexibility of various DERs, and flexibility forecasting predicts demand fluctuations for proactive energy management [115]. Together, these aspects form a comprehensive approach, utilizing AI to enhance demand-side flexibility and lead to more resilient and adaptive energy systems. Fig. 3 illustrates the role of AI in managing and optimizing demand-side flexibility within a smart home environment.

3.1. Flexibility optimization

Flexibility optimization in a smart grid involves maximizing energy

Table 2
Supervised learning approaches for demand-side flexibility.

Model	Graphical Representation	Flexibility Roles	Limitations	Research Articles
Linear Regression ■ A model that establishes a linear association between an independent and a dependent variable.		■ Allows for better energy demand forecasting and grid balancing. ■ Identifies flexibility correlations to understand consumer behavior better	■ Assumes linearity. ■ Sensitive to outliers. ■ Limited in modeling complex interactions.	[38–43]
Random Forest (RF) ■ A decision tree-based model that uses multiple trees to improve the accuracy of predictions.		■ Identifies patterns and trends in energy demand. ■ Forecasts energy demand and analyzes customer behavior. ■ Supports informed decisions on demand-side management.	■ Computationally intensive with large trees and data points. ■ Often leads to overfitting multiple decision trees.	[44–53]
Support Vector Machine (SVM) ■ A linear classifier model that uses a hyperplane to separate data into different classes.		■ Segments of customers based on energy consumption patterns. ■ Optimizes load shifting to reduce peak demand and energy costs. ■ Forecasts energy consumption patterns.	■ Sensitive to choice of kernel function and its parameter. ■ Not suitable for large, noisy datasets. ■ Memory requirement issues	[46,52, 54–61]
Extreme Gradient Boosting (XG-Boost) ■ An ensemble method that combines multiple weak models to form a stronger model.		■ Supports optimized energy pricing and tariffs to encourage off-peak energy usage. ■ Outperforms traditional forecasting methods in energy demand forecasting. ■ Optimize energy management systems and reduce peak energy usage.	■ Computationally intensive with large datasets. ■ Less interpretable than simpler models. ■ Requires proper regularization.	[46,62–66]
K-Nearest Neighbours (KNN) ■ The algorithm classifies a new data point based on the majority class of its k-nearest data points.		■ Classification of energy consumption patterns ■ Clustering of households based on energy usage. ■ Integration of smart meter data for improved demand-side management.	■ Performance impacted by parameter k. ■ Ineffective in high dimensions.	[38,56,67, 68]

efficiency, reducing peak demand and energy costs, and improving user comfort. This is achieved by scheduling flexible loads and optimizing energy utilization [116]. Aggregators provide signals to help customers optimize energy use and initiate load shifting for efficient energy consumption. Precise optimization problem definition and integration of user- and system-controlled measures are critical to achieving flexibility optimization [122]. The key control objectives in flexibility optimization include minimizing energy consumption, maintaining thermal comfort, reducing operating costs, and minimizing thermal discomfort hours. These optimization processes can be single- or multi-objective.

Deep learning techniques are effective in flexibility optimization for complex multi-objective optimization scenarios, where factors like energy costs, peak demand, and user comfort need to be balanced [123]. Data-driven predictive control (DPC) methods use historical data and machine learning techniques to optimize building energy efficiency and smart appliance scheduling. Factors such as lighting, ventilation,

occupancy changes, and local climate have a significant impact on the energy efficiency of a building [124]. The integration of generative pre-trained transformers (GPT) with maximal frequent itemset mining has the potential for demand-side flexibility such as by automating the identification of energy waste patterns in building operations. This approach reduces the need for human intervention in analyzing large datasets, thereby improving the efficiency and accuracy of energy management systems [125]. By utilizing abundant data and computing power, data-driven strategies improve control methods by developing dynamic building models for model predictive control (MPC) and RL-based policies.

3.1.1. Appliance scheduling optimization

In appliance scheduling optimization, AI is utilized to strategically operate flexible appliances, reducing energy consumption and grid demand. An appliance control system manages the appliance operation

Table 3
Unsupervised and reinforcement learning approaches for demand-side flexibility.

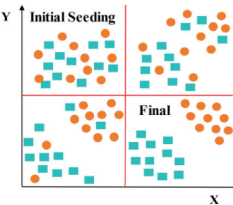
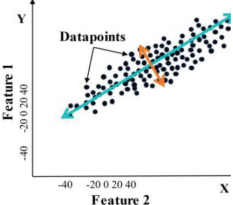
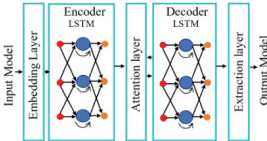
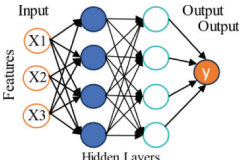
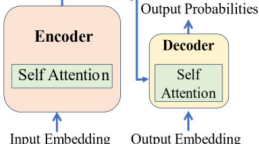
Learning Technique	Model Name	Graphical Representation	Flexibility Roles	Limitations	Research Article
Unsupervised Learning	K-means Clustering ■ A model that groups similar data points based on their features		■ Cluster-based optimal scheduling of the flexibility services ■ Identify opportunities for demand response. ■ Forecast energy consumption and peak load demand.	■ Assumes spherical, equally sized clusters. ■ Requires a predefined number of clusters.	[56, 69–74]
	Principal Component Analysis ■ A model that reduces the dimensionality of data while preserving important features		■ Identify the variability in demand data for quantification. ■ Reduces data dimensionality and identifies the underlying patterns in flexibility data	■ Sensitive to scaling ■ Does not capture nonlinear relationships. ■ Loses interpretability as dimensions are reduced	[75–77]
Reinforcement Learning	Q-Learning and others ■ A model that learns to make decisions based on rewards and penalties		■ Determine the optimal price for energy. ■ Identify the most cost-effective times to shift energy use. ■ Used for predictive load management.	■ Requires extensive exploration. ■ Dependent on reward function design. ■ Struggle with large action spaces.	[78–90]

Table 4
Deep learning approaches for demand-side flexibility.

Model	Graphical Representation	Flexibility Roles	Limitations	Research Article
LSTM ■ Memory cells and gates capture long-term dependencies in sequential data. The input, forget, and output gates control the flow of information to the next LSTM cell.		■ Make predictions for future demand and manage energy generation. ■ Trained to identify specific events, such as holidays, that may impact demand. ■ Model the interplay between energy demand and supply ■ Predict energy consumption and optimize energy management systems. ■ Support the integration of renewable energy ■ Analyze complex consumer data to identify hidden patterns.	■ Complex architecture and difficult to interpret. ■ Requires large amounts of data ■ Prone to overfitting on small datasets.	[44,50,57,75,84, 94–104]
Artificial neural networks (ANN) and its variants - CNN, PINN, RNN ■ Inspired by the human brain, ANN uses interconnected nodes to process information and adjust weights to reduce error.		■ Useful in forecasting scenarios with noisy historical data. ■ Captures long-range dependencies in time-series data.	■ High computational cost. ■ Lacks interpretability. ■ Prone to overfitting, where data is not diverse enough.	[46,49,51,52,55, 56,58–60,72,85, 94,95,98,99, 102–117]
Transformer/Attention mechanism ■ Processes data sequences in parallel/ enhances model focus on relevant parts of input data.			■ High computational cost and model complexity. ■ Requires careful tuning.	[66,96,118–121]

based on scheduling algorithms and various inputs with a user interface that allows users to interact with the scheduling system and input their preferences [126]. Techniques such as load shifting help manage energy demand by adjusting the appliance operation to off-peak times or temporarily disconnecting certain loads [127,128]. Scheduling optimization involves adjusting the indoor temperature of HVAC, coordinating EVs, and battery storage system scheduling, which is important for integrating distributed energy resources and optimizing grid services

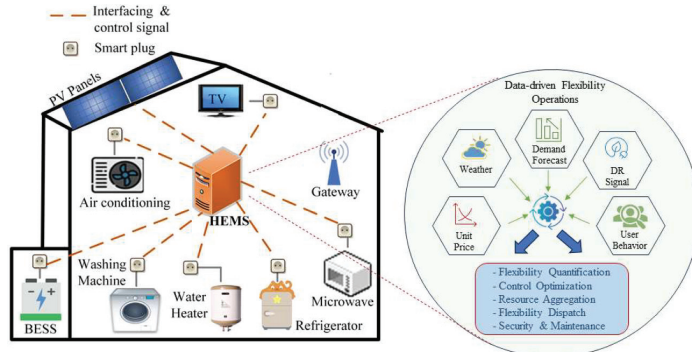


Fig. 3. AI-enhanced smart home environment for optimized demand-side flexibility operations.

[129].

In [130], an inverse reinforcement learning (IRL) model for appliance scheduling is presented, achieving a mean absolute error as low as 0.021 across different days by learning user preferences from past consumption data without explicit input. In comparison, an ANN model reduced average electricity cost by 28.67 % for scheduling EVs and flexible appliances [99]. Similarly, [96] proposed a hybrid LSA-ANN, while [106] utilized DA-GmEDE – ANN models for minimizing energy cost and peak-hour energy consumption for shiftable loads. In [34], SVR and k-means are used with NSGA-II optimization for energy cost reduction and comfort improvement in smart homes. RL-based algorithms for the dynamic pricing of the service provider and consumption scheduling of multiple customers are proposed by [131]. By leveraging the learning capabilities of service providers and customers, an optimal schedule was derived from the empirically observed retail price. Furthermore, a proximal policy optimization (PPO)-DRL agent has been developed to optimize capacity scheduling in PV-battery storage systems, effectively handling continuous action spaces and maximizing net revenue through safe scheduling schemes [124].

3.1.2. Energy optimization

Building energy consumption prediction models provides energy conservation by optimizing energy efficiency through improved insulation, efficient systems, renewable energy, and smart technology [132]. Machine learning algorithms enhance these models by identifying energy-saving opportunities and managing battery storage systems using energy prices, consumption data, and grid conditions to optimally control battery charging or discharging, HVAC systems, and other flexible loads [133]. These algorithms balance energy savings with user comfort by improving occupant behavior, which necessitates careful data-driven strategies [134].

In [108], an adaptive ANN-based MOC model is developed to predict air temperatures in office and lecture settings, integrating with hybrid optimization for maximum energy efficiency and indoor comfort. The proposed approach outperformed the PID-based thermostat control system, reducing 58.5 % and 36.7 % in both settings. A DPC approach with random forests is introduced in [94], achieving a 24.9 % reduction in cooling energy consumption and a 72.0 % decrease in violations of comfort constraints. Furthermore, [135] utilized a machine learning-driven robust model predictive control framework for sustainable multi-zone buildings, which reduced electricity costs by 6.9 % while improving thermal comfort and system stability by addressing weather forecast uncertainties. Similarly, [83] used LSTM-PSO and recorded a 9.41 % energy saving. A DRL-aided bi-level multi-period BES expansion strategy was also proposed in [136], which leveraged a rainbow agent with quantile regression to improve planning efficiency and scalability for microgrid operations [137]. developed an

approximate MPC algorithm based on time-delay neural network (TDNN) and the regression tree algorithms. The research in [138] introduced a novel approach using multi-agent deep reinforcement learning (MADRL) with an attention mechanism in the centralized critic for efficient energy management in interconnected multi-energy microgrids. A comprehensive overview of articles focused on ML-based appliance scheduling and energy optimization for demand-side flexibility is presented in Table 5.

Table 5 shows that hybrid approaches, which combine traditional machine learning models with optimization techniques, have effectively enhanced energy management and cost efficiency across various flexibility domains. For instance, ANN-based models, when integrated with Grey Wolf differential evolution or MPC, achieve significant cost savings and enhanced energy efficiency. Deep-RL approaches, such as Deep Q-learning and DDQN, excel in optimizing energy consumption and appliance scheduling while maintaining user comfort, underscoring the potential of these models in microgrid and smart grid applications.

In addition to these hybrid approaches, integrating advanced AI technologies like federated learning and Explainable AI (XAI) offers further potential to enhance flexibility optimization. Federated learning enables AI models to be trained across decentralized data sources without sharing data directly, addressing privacy and ownership concerns while aggregating insights for more robust models. Incorporating XAI models such as DeepLIFT, LIME, can improve transparency and trust in AI-driven energy management decisions. XAI ensures that stakeholders can understand and trust the decision-making process, leading to more reliable and fair optimization outcomes.

3.2. Flexibility characterization

Characterizing flexible load in demand-side flexibility involves assessing the associated energy consumption of DERs, their response characteristics, and their adaptability to grid fluctuations. Flexibility is quantifiable through power, energy, and time dimensions, such as the correlation between shiftable energy volume and its cost or the duration of sustainable power change [88]. It also includes relative metrics such as flexibility as a percentage of on-site generation, self-consumption, storage efficiency, demand response potential, and other parameters, including power variation, ramping rate, operation frequency, and a scoring system for overall system flexibility [89]. Flexibility characterization enables aggregators to optimize their asset portfolios by quantifying loads, particularly those capable of responding to energy price fluctuations or offering grid services [90]. This involves categorizing technical aspects of flexibility resources into quantitative, qualitative, and control domains. Integrating these characteristics with ramping capacity, rebound effect, and aggregator activation signals results in the effective utilization of flexible resources in providing grid services

Table 5
Reviewed literature using AI techniques for flexibility optimization.

Purpose	Objective Function	Training Model	Optimization Type	Performance	Studies
Scheduling	Minimize Cost	Prophet	Model predictive control (MPC)	Up to 30 % cost saving	[139]
	Minimize cost with the least user intervention	ANN, Density-based Spatial Clustering	PSO	The average electricity payment is reduced by 28.67 %.	[99]
	Minimize cost while considering comfort and DG	RL	Q-Learning	The computational time for RL and BPSO is 1.34 s and 16.51 s, respectively.	[72]
	Reduce load peaks, energy costs, and user discomfort	Deep-RL	Deep Q-learning, deep policy gradient	DPG performed better than deep Q-learning.	[73]
	Minimize cost, peak-to-average ratio	ANN	Grey wolf differential evolution	DA-GmEDE strategy outperforms by 33.3 % in terms of efficient energy management	[106]
	Energy cost reduction and reducing discomfort	ANN, K-means	NSGA-II	The proposed solution gives a 51.4 % cost reduction	[34]
	Reduced computational and energy cost function	Batch-RL	Markov decision process (MDP)	Batch-RL outperforms due to improved cost function and reduced state-action space.	[140]
	Reduce cost without violating thermal comfort	BNMI- ANN	MPC	MPC saves operating costs between 6 % and 73 %, depending on the season	[141]
	Minimize energy consumption	RNN, ANN	MPC	Both RNN and MPC saved 18 % more energy compared to ANN controllers.	[113]
	Optimize heating demand and natural gas consumption	ANN, decision tree, gauss process regression	MPC	GPR-based MPC reduced 22.2 % natural gas consumption and 4.3 % building heating demand.	[142]
	Optimize energy carriers to reduce grid dependency	RL	Fitted Q-iteration (FQI)	Grid interaction is lower in RL as compared to the baseline model	[71]
	Reduce operational costs while maintaining user comfort	GC-LSTM	Dueling-DDQN	The dueling-DDQN is more effective in reducing user costs without affecting user comfort.	[143]
	Energy cost reduction by decreasing user discomfort	Deep-RL	Actor-critic, Q-learning	Deep-RL performs better on sunny weekdays with 0.55 EV SOE	[78]
	Minimize cost by reducing energy consumption	Deep-RL	Deep Q-learning, DDQN	DDQN minimizes the cost rate to 28.5 % less than PSO	[144]
	Maximize self-energy consumption and reduce costs.	RL	Policy iteration (PI), FQI	PI outperforms FQI with a 7.2 % increase in PV consumption	[70]
	Optimize temperature set-point and minimize costs	LSTM	Gradient descent (GD)	the proposed strategy outperforms other strategies in reducing the HVAC energy cost	[86]
Energy	Minimize energy use and maintain thermal comfort	LSTM, regression model pool	PSO	NRMSE of chillers is 0.124 and 0.117. Energy saving ratio was 9.41 %	[83]
	Minimize energy use while constrained on user comfort	RL, SARIMA	Optimal policy and hybrid ant-colony optimization	Energy consumption was reduced by approximately 27 %	[64]
	Optimize the heating demand, operational temperature	RL	Q-learning	RLC provides 10 % energy saving while maintaining operational temperature	[74]
	Optimize the temperature set points to minimize energy use and cost	ANN	GA	ANN CVRME is around 2 %. Shifting load reduces energy costs by 27 %.	[107]
	Optimize energy and indoor thermal comfort	NARX-ANN	MPC	The ANN-MPC reduces 58.5 % and 36.7 % cooling thermal energy consumption in the office and lecture theatre.	[108]
	Minimize energy consumption and maximize user comfort	Regression tree and LS-Boost	DPC	DPC-LS-Boost outperformed the DPC-RT and (MPC, TDNN) in performance and scalability.	[51]
	Optimize temperature set-points to minimize energy consumption	Random forests	DPC	24.9 % reduction in cooling energy consumption and 72.0 % less comfort constraint violations	[94]
	Minimize energy consumption while maintaining user comfort.	Distributed-RL	DPC	DRL reduces overall energy consumption by 6.72 % and 3.67 %	[75]
	Optimize cooling water systems to reduce energy consumption and operation costs.	Deep-NN	Epsilon-constrained differential evolution with random jumping-II	Operating costs and primary energy consumption were reduced by >10 %/day	[109]
	Minimizes energy demand peak and consumer bills	Deep-RL	Epsilon greedy policy, Deep Q-network	Deep-RL reduced electric bills by 13.2 % and peak demand by 3 %, while MILP reduced bills only by 3.3 %	[69]
	Optimize the total energy cost	Decision tree	Mixed integer programming (MIP)	A decision tree-based dispatch strategy saves an average of 30 % on total generation cost.	[117]
	Reduce energy consumption and improve comfort	Deep-RL	Gradient Descent optimizer	DRL achieved 8 % more energy savings, reaching up to 16 % in summer savings.	[52]
	Optimize energy resources management to maximize profit	Deep-RL	DQN, Actor-critic, A3C, Proximal policy optimization	A3C outperforms the rest of the algorithms by yielding 50 % profit of the optimal controller.	[100]
	Optimize distributed energy assets to maximize profits	Deep-NN, RL	Soft Actor Critique	Deep-RL outperforms the conventional algorithms	[87]
	Optimize energy efficiency while maintaining thermal comfort in buildings	Transformer Neural Networks, CNN, LSTM	Non-AI conventional methods	Transformer model yielded 50 % energy savings compared to other models	[101]
	Optimize energy consumption to facilitate demand response	Multi-agent DRL	Actor-critic algorithm with shared attention mechanism	6 % net load demand reduction compared to standard reinforcement learning approaches	[145]

[146]. The flexibility function quantifies the capacity of a building to adapt to changing grid demands through the flexibility index. This index considers the dynamic relationship between an aggregator penalty signal and the responding demand adjustments [147]. Fig. 4 illustrates

the characteristics of flexible loads and their interconnected attributes.

Regarding the role of AI in flexibility characterization, [54] utilizes feature engineering and a NILM algorithm to disaggregate electricity consumption data while focusing on appliances that offer flexibility in

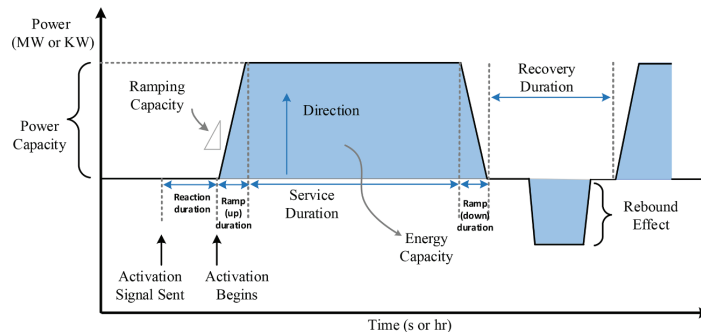


Fig. 4. Characteristics of flexible resources.

DR programs. The results show that AI algorithms, such as random forest and k-means, provide more accurate disaggregation and flexibility results. In [118], an XG-Boost-based non-intrusive method analyzed the energy flexibility of residential buildings by analyzing the consumption patterns, power value distribution, and starting time distribution of flexible appliances, yielding up to a 25 % peak-to-average consumption reduction in a DR model. Similarly, [119] quantified heat pump pool flexibility using energy and time duration until the energy consumption of the activated pool drops below baseline operation levels. In [148], a dynamic two-stage optimization model enhances flexibility by optimizing resource selection and coordination through submodular optimization, achieving up to 97 % performance efficiency in various scenarios. An overview of articles focused on ML-based flexibility characterization for demand-side flexibility is provided in Table 6.

In Table 6, it is clear that traditional machine learning models perform better in characterizing flexibility when combined with other methods. For instance, XG-Boost and k-means clustering are effectively used to assess flexibility and create demand response (DR) profiles. Reinforcement learning models use dynamic pricing signals to learn optimal policies, resulting in significant cost savings compared to baseline controls. Additionally, deep learning models such as GRU and ensemble methods, like combining random forests with neural networks demonstrate effectiveness in managing the complexities of HVAC, PV, and energy storage systems.

The efficiency and applicability of the AI-driven flexibility characterization model can be enhanced by applying transfer learning. A model trained on data from HVAC systems can be fine-tuned using a smaller dataset from a similar but different system, like a heat pump. This will reduce the need for extensive retraining while maintaining high accuracy in new applications. Similarly, using autoencoders for dimensionality reduction, followed by clustering, can improve the identification of complex patterns in energy usage data, leading to more precise demand response profiles.

3.3. Flexibility forecasting

Energy flexibility forecasting predicts adjustable energy quantities to match fluctuating demand or supply. It helps aggregators manage customer energy and enables consumers to participate in energy markets [102]. Various forecasting types, such as electric and thermal load, renewable energy generation, and energy price, contribute to this process. These methods assist in optimizing renewable energy consumption, minimizing customer discomfort, and making informed energy market decisions [103]. AI improves flexibility forecasting by automating large-scale data analysis and predicting future energy demand. Accurate day-ahead and hour-ahead predictions offer insight into energy-shifting flexibility and associated costs. These forecasts are essential for aggregators to expect customer response to flexibility activation signals and avoid penalties [104].

Regarding the role of AI in flexibility forecasting [44], presented a peak and valley load forecasting model using LSTM [40]. focused on forecasting inner temperature and price for residential areas over a two-hour horizon, utilizing weather and occupancy data to train decision trees and regression tree algorithms [105]. proposed hourly energy consumption forecasting of an educational building using GA-triggered LSTM and compared the results with PSO-triggered FFNN using MAE, RMSE, and R^2 evaluation indicators. Similarly, [97] demonstrated that a two-layer ANN could accurately forecast the demand flexibility of aggregated residential loads with just 5 % smart meter coverage [67]. assessed the effectiveness of two forecasting algorithms in predicting building consumption [81]. uses a transfer learning model combined with TFT to improve the prediction of load demand in buildings with limited historical data. Regarding battery state of charge (SOC) estimation [154], proposed temporal-frequency dual attention mechanism network (TFDAMN) to encode time-domain features and capture complex dependencies [155]. utilized transformer-based architecture (ComfortGPT) that employs pre-trained models to capture diverse range of thermostatic preferences to predict user temperature setpoints. Table 7 summarizes the reviewed literature that utilizes AI techniques for flexibility forecasting.

According to Table 7, deep learning models have outperformed traditional machine learning models in various forecasting tasks applied across different demand sectors. For instance, LSTM models have consistently demonstrated superior performance in both thermal load and electricity consumption forecasts, highlighting their capability to handle nonlinear patterns and long-term dependencies. ML models, particularly those enhanced with optimization algorithms (e.g., GA-enhanced LSTM), also show strong performance, especially in residential and commercial electric load forecasting. SVM, when combined with clustering techniques like k-means, provides competitive accuracy in commercial settings.

To improve forecasting accuracy, combining LSTM temporal capabilities with CNN spatial pattern recognition strengths and using ensemble methods like stacking to merge multiple model strengths can provide a more reliable solution. Incorporating deep feature synthesis and uncertainty estimation methods, such as Bayesian neural networks or Monte Carlo dropout, into flexibility forecasts is also beneficial. This is particularly valuable in microgrid energy management, where decision-making often needs to consider uncertainty. Similarly, transformers, originally designed for natural language processing, have shown promise in time-series forecasting tasks relevant to energy management due to their ability to capture long-range dependencies and contextual relationships

Table 6
Reviewed literature using AI techniques for flexibility characterization.

Flexible Resource	Training Model	Model Type	Insights	Quantification Performance	Studies
Shiftable appliances	Ada-Boost, KNN, linear regression, SVM	Historic real-world data experiment	A 3D surface is developed, spanned by time, power levels, and the corresponding maximum sustained duration of flexible loads by considering PDFs by applying various ML methods	Ada-Boost outperformed with MAE and R ² of 21 and 0.94, respectively	[38]
HVAC	ANN-multi-layer perceptron	Modelica for HVAC, EnergyPlus twin model simulation	A framework for simulating established models to assess DR potential quickly is built and determined using a set of indices with two common strategies.	R ² above 0.9 reveals the dynamics of DR programs under different scenarios.	[98]
Shiftable appliances and equipment with PSC	XG-Boost, k-means	Historical benchmarking estimation model	XG-Boost estimates the flexibility (Peak Shaving Capacity), and k-means creates DR profiles to find the percentage of baseline power consumption during DR events.	The model achieved R ² of 0.92 and MSE of 0.004 in estimating the power-shaving capacity.	[49]
HVAC	Soft actor-critic (SAC), Deep- RL	EnergyPlus archetype model simulation	RL automates building EMS, enabling energy flexibility from passive thermal mass. SAC agents learn optimal control policies when given dynamic pricing signals.	RL model achieves cost savings of 9.7 % compared to the baseline control	[149]
Heat pump and thermal storage system	M5P decision tree algorithm, linear regression	EnergyPlus co-simulation calibrated on ASHRAE	By designing, developing, and testing an EMS, DR-based flexibility capabilities are provided for residential buildings	39 % and 37.9 % reduction in utility generation and carbon emissions	[40]
Shiftable appliances, EV	XG-Boost	Data-driven simulation using real-world data	Flexibility is quantified by analyzing power and start-time distribution of shiftable appliances based on non-fixed power values and consumer usage behavior using smart meters	Peak-to-average consumption reduced by up to 25 %	[50]
Controllable and uncontrollable load	2-layer ANN	Data-driven simulation using real-world data	ANN disaggregates the total forecasted load to illustrate the effect of smart meters (with sub-metering functionality) coverage on the accuracy of demand decomposition	AWFE is around 10 % of the average monthly load, ARIMA shows a 20 % larger error	[97]
Individual heat pump	LSTM, GRU, RNN	Data-driven simulation using real-world data	The duration of a heat pump in forced-on or off mode is measured by comparing predicted flexibility based on temperature forecasts and indoor temperatures.	GRU outperformed in flexibility prediction ($c = 16, m = 16$), followed closely by LSTM	[39]
Shiftable loads	K-means	CPLEX software model simulation	An aggregated load model is formulated based on the representative clusters obtained using adaptive k-mean by effectively managing flexible loads.	Cluster-based modeling performed better than random aggregation.	[63]
EV	Clustered multi-node Gaussian Process (CMNL-GP)	Data-driven simulation using real-world data	CMNL-GP leverages multi-task learning to capture the between-node similarities and estimate the node-specific randomness for EV charging flexibility in multi-node power distribution systems.	CMNL-GP outperforms the LR, ARIMA, SVM, and ANN by 8.20 %, 7.90 %, 6.80 %, and 3.80 %, respectively.	[150]
Renewable resources, energy storage, HVAC	MLR, SVR, backpropagation NN	Data-driven simulation using real-world data	A surrogate model-based controller simplifies building energy prediction and improves computational efficiency. By using short-term prediction and predicted control, energy flexibility is enhanced.	The proposed model shows an NMBE of <10 %, with building peak power reduced by 21.9 %	[151]
HVAC, PV, BESS	Random Forest, MLP-NN, SVM, XG-Boost	EnergyPlus co-simulation calibrated using ASHRAE standards	A data-driven DR model utilizes storage capacity and efficiency to characterize the flexibility potential by considering weather, end-user preferences, and power profiles of building energy conversion systems	The ensemble prediction model outperforms the constituent base learners	[152]
Washing machine, dishwasher, and tumble dryers	G-means	LINEAR pilot site data simulation	Characterize individual customer flexibility profiles regarding configuration time and deadline to exploit flexibility via clustering, which can be influenced by various factors such as the day of the week.	Bayesian-based MCMC is identified to be an appropriate regenerative model.	[59]
Flexible appliance	Minibatch k-mean	Data-driven simulation using real-world REDD dataset	ILM method extracts appliance states, power consumption, and usage patterns and calculates appliance flexibility based on historical data, measurement uncertainty, and user behavior.	The proposed method shows an f-score of 0.9 compared to a semi-supervised learning method.	[61]
Flexible load	FCNN, LSTM, decision tree, SVM	Data-driven simulation using real-world data	A digital platform is designed to perform energy prediction and building flexibility detection through prediction and classification tasks, incorporating a collaborative approach to improve multi-class classification accuracy.	For forecasting, LSTM performs better in terms of both MSE and MAE, while overall SVM accuracy is 91.3 %	[153]

4. Discussion and evaluation

4.1. AI flexibility performance framework (AFPF) for demand-side flexibility

The integration of AI has shown significant potential in the rapidly evolving field of energy flexibility. However, a critical gap exists in

standardizing the evaluation and comparison of diverse AI methodologies used for similar tasks. To address this, a set of baseline assessment parameters is required to create a standardized framework for evaluating the effectiveness and applicability of AI-accelerated flexibility techniques in consumer and market settings.

Based on this foundation, the AI Flexibility Performance Framework (AFPF) is proposed as an initial proposition to provide a consistent

Table 7
Reviewed literature using AI techniques for flexibility forecasting.

Objective	Demand Sector	Quantitative Factor		Data Analysis		AI Model	Forecasting Performance	Studies
		Weather	Occupancy	Pre-Processing	Feature Selection			
Electric Load	Residential area	✓		✓	✓	GA-Enhanced LSTM	Model shows RMSE of 0.61 % for short term and of 0.56 % for medium-term.	[84]
Electric Load	Commercial area	✓			✓	SVM, FFNN	SVM performs better than FFNN with MAPE=1.90 % and RMSE=3.3 %	[45]
Electric Load	Commercial building	✓		✓	✓	ESN, FFNN, K Mean (Load Clustering)	ESN performs better than the traditional FFNN model	[62]
Electric Demand	Commercial, residential building	✓	✓		✓	LSTM	LSTM performs better for each heating, cooling, and intermediate season	[85]
Thermal Load	Commercial building	✓	✓	✓	✓	NARX Recurrent Neural Network, ϵ -SVM-R	the NARX RNNs outperformed the ϵ -SVM-R models based on the MAE and MSE	[46]
Thermal Load	Commercial building	✓	✓	✓		LSTM, regression model pool	LSTM prediction is better than the regression model	[83]
Peak Load	Residential area	✓		✓	✓	Deep Bi-LSTM S2S, LMBP-ANN, shallow LSTM S2S	Deep Bi-LSTM S2S model has outperformed all other models on both public holidays and normal days.	[95]
Indoor Temperature	Residential building	✓	✓	✓	✓	LSTM and Gated Recurrent Unit (GRU) RNN	Outperforming GRU by over 9 % lower RMSE, LR models by 32 % lower RMSE	[39]
Electric Appliance Consumption and Peak Demand	Residential household			✓	✓	CLARA, SVM, ANN	SVM provides the outcome of 99.6 % accuracy compared to others	[47]
Air Conditioners Load	Residential building	✓				LMA-ANN, Multiple Linear Regression	LMA-ANN shows 94.43 % MSE and 97.00 % MAPE, which is much higher than multiple linear regression	[120]
HVAC Load	Residential building	✓	✓	✓	✓	XG-Boost, Linear, Lasso Regression, Wrapper Backward Elimination	XGBoost provides the most accurate forecast	[66]
Power Consumption and Renewable Energy Generation	Smart building	✓		✓		Random Forest and Decision Tree	The decision tree method performs better than Random Forest.	[53]
Out-Door Temperature	Residential household	✓	✓	✓	✓	GC-LSTM	GC-LSTM shows an RMSE of 0.897 when compared with actual values	[143]
Air Conditioners Load	Office space	✓		✓		Hybrid ARIMA-MetaFA-LSSVR, ARIMA,	The proposed system obtained a total error rate of 4.8 % compared with other models.	[156]
Electricity Consumption	Campus building	✓	✓	✓	✓	ANN, Linear Regression	ANN method maintains higher stability when predicting consumption on working days	[43]
Energy use Intensity	Residential buildings		✓	✓	✓	Multivariate Linear Regression	The model predicts savings between 16 % and 28 % with R ² of 0.40	[42]
Power Consumption	Residential household			✓	✓	CNN, SVM, ANN	CNN outperforms by 0.59 % and 0.79 % of MAE and RMSE	[48]
Home Appliances Consumption	Residential household	✓		✓	✓	PCA, DNN, SVM	In all forecasts, DNN outperforms the SVM formulation	[77]
Electric Load	Distribution area	✓		✓	✓	PCA, KELM, Fireworks Algorithm (FWA), BPNN, SVM	FWA-based KELM-PCA model outperformed SVM and BPNN in load forecasting	[76]
Wind Speed	Distribution area	✓		✓	✓	GNN, LogSparse Transformer	Proposed model outperformed LSTM and MLP models	[157]

benchmark for AI-accelerated flexibility approaches. The framework is guided by the primary objective of balancing technological advancements with consumer-centric approaches. The AFPF comprises two main components: the Business-to-Consumer (B2C) Flexibility Index and the Consumer Relevance Indicator. The B2C Flexibility Index determines which studies provide actionable insights for developing practical flexibility models for the energy market. The Consumer Relevance Indicator focuses on evaluating the effectiveness of studies from the consumer perspective, considering their user-centric approach and customization potential.

Fig. 5 enlists the AFPF evaluation criterion for assessing the performance of different flexibility aspects. A binary reward mechanism is

employed, where each AI-accelerated flexibility model is awarded based on properties covered in the studies. AFPF serves as a starting point for standardization in the field, with the main purpose of establishing a foundation for further research and validation.

To provide the context and potential application of the AFPF, the paper applies the framework to various AI-driven flexibility studies, as shown in Table 8.

The assessment of AI-accelerated flexibility models highlights distinct trajectories in their application across various domains of demand-side flexibility, as illustrated in Fig. 6. Among consumer relevance indicators, energy savings and economic viability are the most frequently addressed criteria, with 27 % and 25 % of studies focusing on

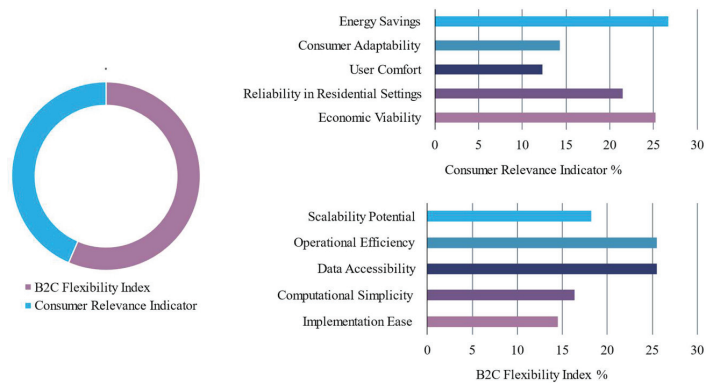


Fig. 5. Overview of AFPP assessment criterion for AI applications.

Table 8
Demonstration of the use of AFPP in evaluating the performance of AI-accelerated flexibility models.

Article	Flexibility Aspect	Consumer Relevance Indicator					B2C Flexibility Index				
		a	b	c	d	e	a	b	c	d	e
[38]	Characterization	★	★				★	★	★	★	★
[158]	Characterization		★		★	★		★	★	★	
[121]	Optimization	★	★	★	★	★				★	
[159]	Forecasting	★			★	★	★	★	★	★	★
[160]	Optimization		★		★	★	★	★	★	★	★

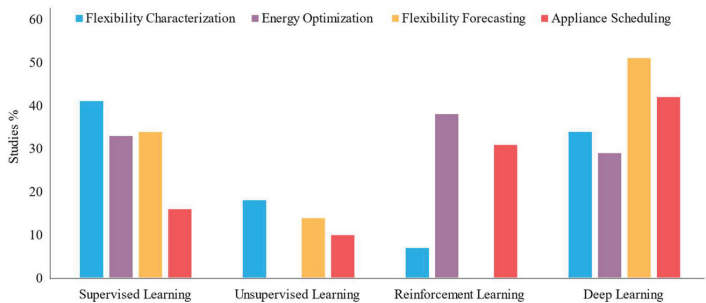


Fig. 6. Aggregated representation of the prevalence of each criterion within the assessment indices.

them, respectively. In contrast, consumer adaptability and user comfort are less extensively covered. Within the B2C flexibility index, operational efficiency and data accessibility are the most represented criteria, highlighted in 51 % of the studies. Conversely, computational simplicity and ease of implementation have the least representation, reflecting the inherent complexity of AI models and the challenges associated with

their implementation.

Fig. 7 illustrates the distribution of AI learning techniques across flexibility domains. Supervised machine learning models are widely used in flexibility characterization, accounting for 41 % of the research. For energy optimization, the distribution includes 33 % supervised learning, 38 % reinforcement learning, and 29 % deep learning. Deep

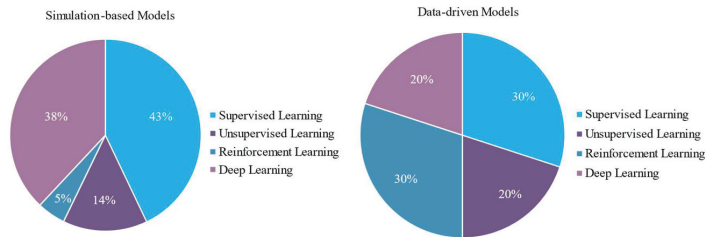


Fig. 7. AI techniques in various areas of demand-side flexibility.

learning methodologies have become prominent in flexibility forecasting, utilized in 51 % of the reviewed papers. LSTM models have demonstrated high precision in forecasting peak and valley loads, thermal loads, and electric demand across diverse sectors. In addition, SVM has proven to be an effective tool for accurate short-term and daily load forecasting.

In the reviewed studies, about 32 % of the studies focus on analyzing the flexibility of HVAC systems. Shiftable appliances account for 20 %, followed by heat pumps at 18 %, battery energy storage systems at 16 %, and a combination of EV and photovoltaics at 14 %. Compared to conventional control methods, reinforcement learning methodologies for control tasks do not generally require an environment model. These characteristics offer a significant advantage in developing optimization systems incorporating high-dimensional decision variables, such as customer preferences and appliance operational conditions. Regarding the literature on flexibility characterization, Fig. 8 provides a breakdown of the application of various AI techniques in simulation-based and data-driven models. While supervised and deep learning techniques are prevalent in simulation-based models, data-driven models exhibit a more balanced distribution of AI techniques, with a slight preference for supervised and reinforcement learning.

From the literature, ANN emerges as the most prevalent technique, especially in multiple-horizon forecasting, due to its ability to learn non-linear, complex that involve multiple inputs. While ANN demands significant computational resources and large datasets, supervised learning methods, while less adaptable and more biased than ANN, depend on strong feature selection and engineering to yield favorable outcomes.

5. Challenges and future research direction

While this study highlights the potential of machine learning techniques in enhancing demand-side flexibility, there are several limitations when compared to traditional physical models. For instance, physics-based thermal modeling for HVAC systems can effectively analyze the rebound effect following flexibility provision. ML models lack sufficient data reflecting these complex dynamics, which underscores the need for a hybrid approach, such as physics-informed neural networks that integrate physical and ML models for comprehensive energy management [82]. PINNs are capable of capturing transient and nonlinear behaviors inherent in energy systems more effectively than common data-driven models [161]. ML models typically assume that the underlying data distribution is stationary. However, this assumption is often invalid in dynamic, flexible energy systems where consumer behavior, weather patterns, and grid conditions evolve due to economic, technological, and policy changes. This results in decreased model accuracy and effectiveness over time as models struggle to adapt to these non-stationary conditions. By embedding physical laws directly into the neural network architecture, PINNs enhance predictive accuracy and robustness, even under non-stationary conditions.

Deep learning models, including federated and interactive learning

models, are highly data-dependent and confined to specific scenarios. The computational demands associated with these models make it challenging to integrate them into real-time energy management systems. The need for continuous model updates to maintain accuracy in dynamic and decentralized demands-side flexibility environments also introduces scalability challenges.

The exploration-exploitation trade-off in reinforcement learning presents challenges when applied to the optimization of scheduling flexible loads and managing energy resources. In dynamic and complex environments, overemphasizing exploration leads to higher initial costs and inefficiencies, while excessive exploitation results in suboptimal long-term performance. An adaptive heuristics approach that leverages the strengths of both ML-based and traditional methods can offer a more comprehensive solution to the challenges of optimizing demand-side flexibility in energy systems by ensuring a reliable fallback strategy.

The AI Flexibility Performance Framework highlights several challenges regarding the complexity of developing AI-based energy flexibility models while maintaining a balance between technological innovation and consumer protection. One of the key challenges is the development of a unified flexibility model that can comprehensively manage all flexible appliances within a household. Current models address individual appliances or systems, leading to complex and less efficient solutions. A holistic model that integrates all household flexibility resources is essential to optimize energy usage and improve user comfort. Similarly, ensuring customer-centricity in AI-driven flexibility models also poses challenges that require the consideration of dynamic consumer behavior towards appliance usage and energy conservation potential. To overcome the challenges related to data privacy, regulatory frameworks, and consumer protection, there is a need to develop a code of ethics for AI in power systems, outlining ethical principles for development and use. Creating a regulatory sandbox provides a safe space for companies to test AI-based energy management solutions without consumer risks. There is a need to establish an AI observatory to track AI evolution and usage in power systems and to identify potential risks, ensuring safe, secure, and fair utilization of AI technology.

The increasing research on DC systems highlights the importance of DC energy flexibility as a potential solution for enhancing energy efficiency and providing ancillary services such as voltage droop control. This necessitates further research into how DC energy flexibility can be utilized for DC grid support functions. By distinguishing between AC and DC flexibility, aggregators can choose the most appropriate solution for each location and provide a wide range of ancillary services to ensure a stable and reliable power grid [162]. Regarding the potential of DC load and energy flexibility in residential buildings, [163] presented an energy management model of PVs, ESSs, and EV charging stations in a hybrid microgrid based on AC and DC buses. Similarly, [164] proposed a controller for ensuring flexibility in energy exchange between the DC source, storage battery, and grid connection via the three-phase DC/AC inverter with a boost converter. Table 9 provides a comparison of AC and DC flexibility.

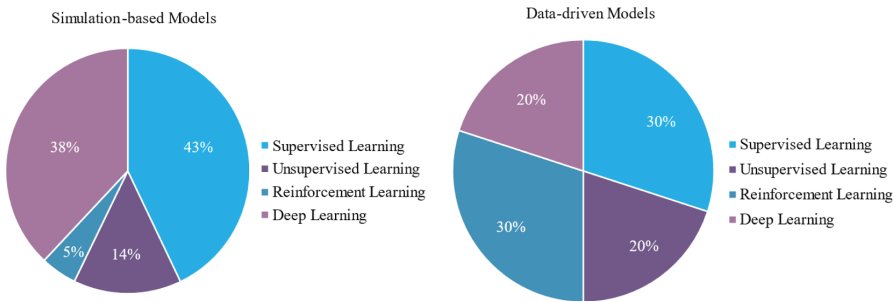


Fig. 8. Comparative analysis of AI model types for flexibility characterization.

Table 9
Differentiating between AC and DC flexibility options.

Feature	AC Flexibility	DC Flexibility
Power	Variable power output	Constant or variable power output
Characteristics		
Examples	HVAC systems, lighting systems, electric water heaters	Energy storage systems, electric vehicles, DC-DC converters
Control	Energy management systems adjust power consumption, scheduling, and demand response based on various inputs, such as weather and grid conditions.	Control of the charging and discharging of the energy storage system to provide grid services and smart controls
Capabilities	Balancing supply and demand, integration of renewable energy sources, and ancillary services	Frequency regulation, peak shaving, load balancing, Voltage and frequency support, Black start capability
Grid Services		Micro-grid and transmission level
Deployment Scale	Micro-grid and distribution level	

Future research should focus on developing AI solutions that are technologically advanced and aligned with business scalability, economic viability, and consumer-centric design. This involves improving the computational efficiency, transparency in decision-making, and adaptability of AI systems to diverse and evolving energy scenarios while addressing energy sustainability goals and regulatory frameworks. Regarding energy flexibility, the application of transformer architectures, with their ability to process entire sequences in parallel using self-attention mechanisms, can significantly enhance the characterization of energy flexibility by capturing complex consumer behavior patterns and optimizing resource allocation. Transformers, predominantly utilized in forecasting tasks, possess comprehensive capabilities that make them highly effective for analyzing and managing demand-side flexibility in dynamic market conditions.

Furthermore, leveraging advanced generative models like diffusion models [165] and generative adversarial networks (GANs) could also significantly improve demand-side flexibility services. Diffusion models, which reconstruct complex data distributions by reversing a noise addition process, can help simulate and predict intricate demand-side flexibility scenarios, aiding in more precise demand forecasting, uncertainty quantification, and resource allocation. GANs and variational autoencoders (VAEs) are valuable for generating realistic energy usage data, and enhancing AI training where actual data is limited or incomplete, thereby improving the robustness and performance of models. For instance, in [166], GANs are utilized to generate synthetic data, thus aiming to reduce the cost of smart metering while providing sufficient information for grid modeling. Similarly, GANs have found applications in PV and wind forecasting [167,168], fault diagnosis [169] and load estimation models [170].

Incorporating transfer learning and XAI into demand-side flexibility can offer valuable future research directions. Transfer learning allows models trained on one task, such as HVAC energy management, to be adapted with minimal retraining to similar tasks in different contexts, thereby improving model efficiency and scalability. This approach can help address the challenge of data scarcity and non-stationary conditions by leveraging knowledge from related domains. XAI enhances the transparency of AI-driven decisions in energy management by providing clear insights into how decisions are made, which is crucial for integrating AI into real-time systems. These approaches can help overcome current limitations and optimize demand-side flexibility in dynamic energy environments.

6. Conclusions

This research presents a comprehensive review of demand-side flexibility, focusing on the capabilities of AI to optimize energy consumption, characterize and quantify flexibility, schedule appliance operations, and forecast flexible demand. The review examines AI-driven flexibility techniques across various matrices, including flexible resources, objective functions, training models, optimization types, and key performance indicators. An AI Flexibility Performance Framework is formulated to evaluate the studies from end-user and industrial perspectives, aiming to identify adaptable and scalable solutions in demand-side flexibility. The AFPF marks the first stage in establishing a

standardized evaluative framework for AI applications in demand-side flexibility. It has identified significant research trends, with 27 % of studies focusing on energy savings from a consumer perspective, while 25.5 % emphasize operational efficiency from an industrial viewpoint. The literature review highlights an increasing focus from industry and academia on energy management research, driven by the growing integration of renewable energy resources toward a more sustainable energy sector. The AFPF serves not only as a benchmarking tool to evaluate the performance of AI-driven flexibility models but also guides future AI applications toward achieving user-centric and economically viable solutions.

CRediT authorship contribution statement

Arqum Shahid: Writing – original draft, Visualization, Methodology, Conceptualization. **Roya Ahmadihangar:** Writing – review & editing, Validation, Funding acquisition. **Argo Rosin:** Supervision, Investigation, Conceptualization. **Andrei Blinov:** Writing – review & editing, Validation, Formal analysis. **Tarmo Korõtko:** Writing – review & editing, Resources, Project administration. **Dmitri Vinnikov:** Writing – review & editing, Validation.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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Appendix 2

Publication II

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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].

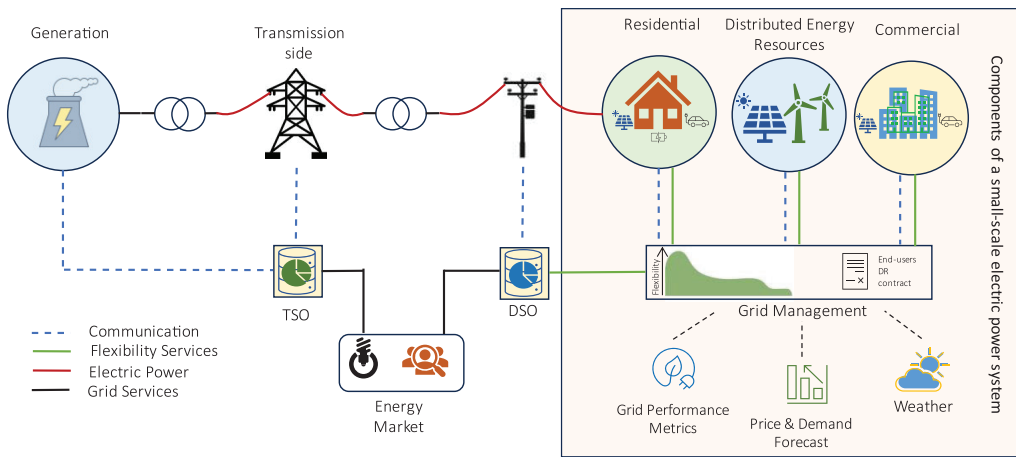


FIGURE 1. Illustration of the structure of a power system.

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, CIDD5 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,
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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

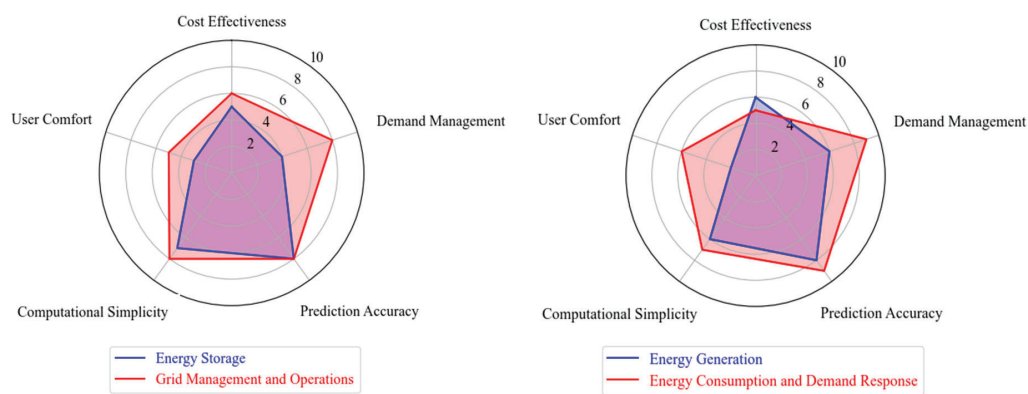


FIGURE 2. Comparative radar charts illustrating the performance of reviewed articles across key quantitative indicators for small-scale electric power systems.

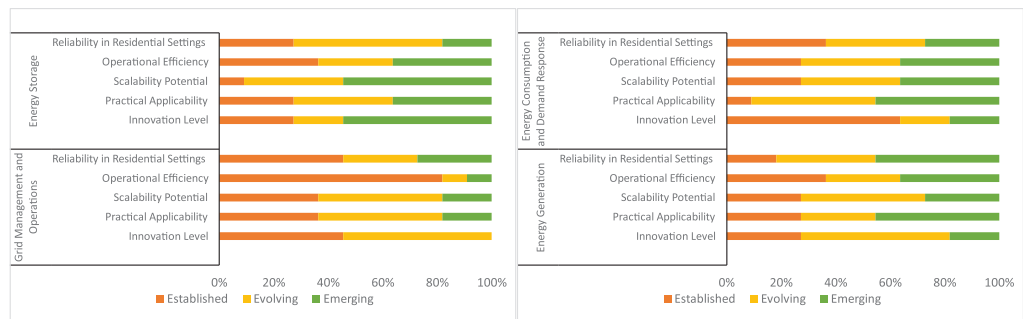


FIGURE 3. Qualitative analysis of AI application across different domains in small-scale electric power systems.

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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management and energy flexibility, crucial areas for the future of energy systems.

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Appendix 3

Publication III

A. Shahid, R. Ahmadiyahangar, J. Kilter, and A. Rosin, "Data-driven quantification and aggregation of demand-side flexibility for symmetrical bidding in energy balancing markets," *Electric Power Systems Research*, vol. 247, p. 111823, May 2025, doi: 10.1016/j.epsr.2025.111823.



Data-driven quantification and aggregation of demand-side flexibility for symmetrical bidding in energy balancing markets

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ABSTRACT

Modern power grids are transitioning towards a net-zero framework with carbon-neutral, and weather-dependent generation, necessitating substantial demand-side flexibility to manage the variability in generation and consumption. This paper introduces a data-driven approach to quantify and aggregate demand-side flexibility for effective participation in the energy balancing market. The methodology applies machine learning algorithms to characterize and quantify flexibility from various household appliances, including shiftable loads, thermostatic devices, and battery storage systems, while considering dynamic usage behavior. The quantified flexibility is aggregated per appliance type across households, generating flexibility profiles for both low and high comfort disturbance zones, enabling a detailed assessment of flexibility potential within a residential community. The aggregated flexibility is then optimized using a sequential Mixed-Integer Linear Programming (MILP) model to maximize utilization while adhering to operational and market constraints, including minimizing user discomfort and fulfilling symmetrical bidding requirements for both up- and down-regulation over the next four-hour pool. Two case studies are presented: the first demonstrates the flexibility quantification of a single household, illustrating dynamic user behavior in appliance usage, while the second presents the aggregated flexibility of multiple households, showcasing community-level potential. The results validate the approach's effectiveness in quantifying and aggregating demand-side flexibility, achieving an average utilization of 82 % from the low comfort zone, thereby reducing user discomfort and facilitating strategic participation in balancing markets.

1. Introduction

Renewable energy sources (RES) integration in energy systems is essential for carbon neutrality. However, the inherent intermittency and uncertainty of RES generation introduce frequent imbalances, and frequency deviations, posing major challenges to grid stability. To maintain frequency within acceptable operational limits, transmission system operators (TSOs) rely on ancillary services such as Frequency Containment Reserve (FCR). While these reserves have traditionally been supplied by large-scale dispatchable generators, the increasing deployment of smart meters and distributed energy resources (DERs) has opened new avenues for demand-side flexibility (DSF) to contribute to balancing services [1]. Residential flexibility sources include shiftable appliances, thermostatically controlled appliances (TCA), and battery energy storage systems (BESS). Shiftable loads delay operation for up-regulation, while TCA and BESS provide both up- and down-regulation, enabling symmetrical regulation capabilities as required in the case of Fingrid's

FCR-N reserve [2]. Modern home energy management systems schedule appliance operation, while aggregators pool and optimize flexibility for market participation.

2. Literature review

Recent advancements in deep learning, including optimized sequence-to-sequence architectures, attention mechanisms, and hybrid ensemble models, have significantly improved the reliability of energy demand and renewable generation forecasts [3–5]. Accurate forecasts serve as foundational inputs to machine learning models that quantify flexibility by identifying consumption deviations and optimization opportunities. Machine learning techniques, leveraging household energy data, offer significant potential in quantifying demand-side flexibility by extracting complex consumption patterns and uncovering appliance interdependencies. In [6], a random forest classifier is used for flexible load disaggregation. K-means clustering generates flexibility curves of

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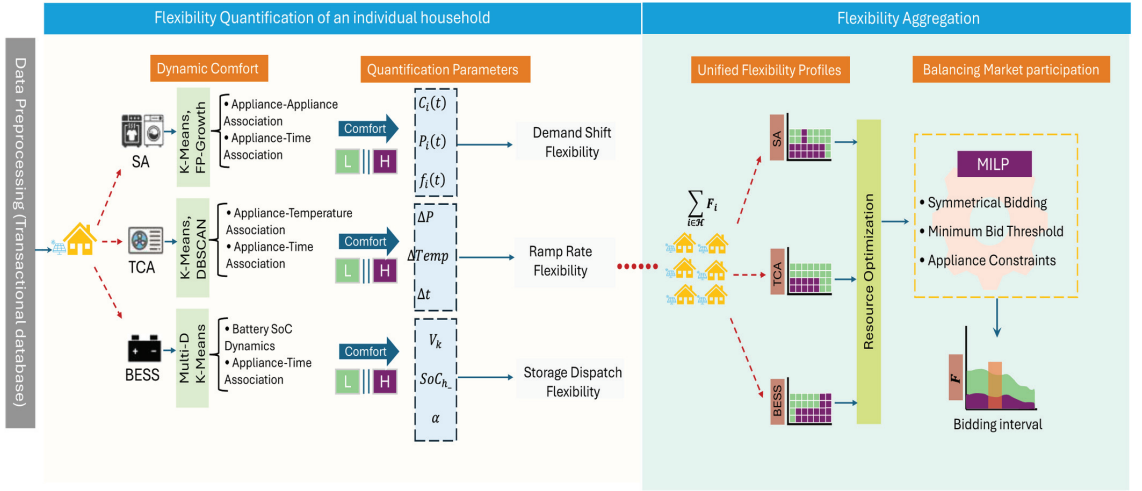


Fig. 1. Proposed flexibility quantification and aggregation framework.

these appliances based on maximum and minimum operating curves. A bottom-up flexibility analysis has been carried out in [7], where a random forest-based forecasting model predicts building-level energy demand, supporting participation in local flexibility markets. In [8], the flexibility of thermal loads is quantified by measuring the difference between a reference and optimal output power. Similarly, [9] developed the flexibility envelopes, spanned by time, power levels, and the corresponding maximum sustained duration of flexible loads by considering the probability density function and predicting it using SVM and Ada-Boost algorithms [10] utilizes electric vehicle charging session data to quantify flexibility using DBSCAN under load flattening scenarios. To extract consumption patterns of shiftable appliances, XG-Boost is utilized in [11]. The energy flexibility is then characterized based on the appliance power value distribution and starting time distribution. In [12], a cloud-based big-data processing technique is developed that targets energy cost in relation to the demand response program to assess the flexibility potential.

Beyond flexibility quantification, research on effectively aggregating flexibility for market participation remains limited. Some studies have integrated flexibility constraints within demand aggregation models, optimizing market participation based on price signals [13,14]. Set-based aggregation frameworks for electric vehicles [15] and ANN-based load demand forecasting methods have provided insights into flexibility potential but remain limited by static compositions and constrained scalability. More dynamic approaches, such as two-stage submodular optimization for virtual power plants [16] and MILP-based multi-microgrid coordination [17], address cost efficiency but do not explicitly quantify flexibility or incorporate user comfort. Cluster-based aggregation strategies relying on MINLP have focused on load scheduling but fail to align with balancing market requirements [18].

Despite the growing interest in utilizing DSF, a critical research gap persists in the quantification and aggregation of flexibility in a way that aligns with the heterogeneity of appliances, user behavior variability, evolving comfort preferences, and stringent balancing market requirements. In the literature, flexibility is mostly quantified by identifying two bounding energy curves for appliance operation but often focuses on individual resource types without considering the heterogeneity of household appliances. Similarly, aggregation models typically consider a single flexibility resource type with fixed composition, overlooking the dynamic constraints of diverse appliances and user

comfort preferences. Achieving compliance with symmetrical bidding requirements for FCR provision, even when there is potential for offering asymmetrical quantities within an aggregation pool, remains a significant challenge.

To address these limitations, a multi-stage, data-driven framework is proposed that combines machine learning-based flexibility quantification with a sequential optimization model to enable residential aggregators to participate in balancing market against FCR. The framework operates in two stages. First, flexibility is quantified separately for different appliance categories using machine learning techniques by considering operational behavior and user comfort preferences. This quantification is performed under two dynamic comfort zones: low and high disturbance tolerance, which are updated weekly based on usage patterns. In the second stage, the aggregated appliance-level flexibility is passed to a sequential optimization layer that coordinates household-level participation while ensuring market compliance. This optimization layer prioritizes low-disturbance flexibility and activates high-disturbance flexibility only when needed, enforcing symmetrical bidding and minimum capacity thresholds for FCR participation. The key contributions are:

- A demand-shift flexibility model characterizes shiftable appliance flexibility by incorporating controllability, time dependencies, and appliance interactions using K-means clustering and FP-Growth for dynamic comfort zone definition.
- A ramp-rate flexibility model quantifies the flexibility of TCAs by identifying energy consumption patterns under varying weather conditions using K-means and DBSCAN clustering.
- A storage-dispatch flexibility model assesses BESS flexibility by analyzing SoC variability with multidimensional K-means clustering, incorporating PV contributions to optimize dispatch under high and low utilization.
- A hierarchical and device-level aggregation methodology then creates unified flexibility profiles using a sequential MLP model, optimizing appliance and household flexibility while ensuring market compliance, including symmetrical bidding and minimum bid thresholds for FCR participation.

The paper proceeds as follows. Section 3 details the proposed methodology, focusing on flexibility quantification and aggregation approach, while Section 4 presents a case study. Section 5 concludes the

paper and outlines future directions.

3. Flexibility quantification

This section presents the flexibility modeling approach for shiftable appliances, thermostatically controlled devices, and household battery energy storage systems. The proposed framework uses appliance usage and weather-related data to infer flexibility potential based on how these variables influence user behavior. Rather than assuming fixed operational margins, the models learn usage patterns and behavioral boundaries directly from historical data. Fig. 1 represents the proposed framework of data-driven flexibility quantification and aggregation methodology.

3.1. Demand-shift flexibility

This phase quantifies the flexibility of shiftable appliances by analyzing their energy consumption patterns in response to aggregator signals. It assesses controllability based on an appliance's ability to adjust operation without compromising user comfort. Flexibility quantification relies on appliance-time association, identifying feasible operating periods, and appliance-appliance association, capturing interdependencies. Dynamic comfort disturbance zones—high and low—are established using historical consumption data, accounting for seasonal variations. A rolling one-year window updates these zones weekly, ensuring adaptability to evolving usage patterns. This approach maintains flexibility accuracy while aligning with real-time behavioral trends for effective balancing market participation.

To classify comfort zones and quantify flexibility, K-means clustering is applied to the weekly segment of energy consumption data $x = \{x_1, x_2, \dots, x_T\}$, where T denotes the total number of data samples within the analysis window. Energy data is first converted into a binary format, and weekly segments are extracted regularly to track user behavior. Weekly segmentation captures recurring user behavior while minimizing the impact of short-term anomalies. Based on silhouette analysis, weeks with sufficient variance are clustered into three categories as optimal for appliance behavior: Cluster 0 (inactivity), Cluster 1 (low disturbance, moderate usage, high flexibility), and Cluster 2 (high disturbance, frequent usage, low flexibility). This classification helps identify user behavior trends, optimizing demand-shift flexibility for balancing market participation.

These comfort zones are expressed using the variable $Comfort(K, w)$, which categorizes appliance usage at different times for flexibility:

$$Comfort(K, w) = \begin{cases} \text{Higher Zone} & | \Delta H_i(t) \in C_{high}^w \\ \text{Lower Zone} & | \Delta H_i(t) \in C_{low}^w \end{cases} \quad (1)$$

where $\Delta H_i(t)$ represents the time difference in the association of appliance i with comfort zones K over time t . The high and low comfort zones for the current week w :

$$C_{high}^w = C_{high,initial} \cup C_{high,updated} \quad (2)$$

$$C_{low}^w = C_{low,initial} \cup C_{low,updated} \quad (3)$$

where $C_{high,initial}$ and $C_{low,initial}$ denotes the initial comfort zones based on historical data, while $C_{high,updated}$ and $C_{low,updated}$ incorporate recent user behavior updates.

The appliance-appliance association is analyzed through frequent itemset mining and association rules. The association strength γ which reflects the conditional probability of one appliance being active given that another is also active, is derived using the FP-Growth algorithm. This algorithm efficiently extracts frequent patterns without exhaustive candidate generation, relying on a continuously updated transactional database D comprised of transactions $\Gamma = \{I_1, I_2, \dots, I_k\}$, where each I_i (where $1 \leq i \leq k$) represents a distinct appliance. A simplified trans-

actional matrix is given as:

$$D = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \quad (4)$$

where rows represent transactions and columns indicate appliance states. The support of an itemset X is given by:

$$support(X) = \frac{\text{Number of transactions containing } X}{\text{Total number of transactions in } D} \quad (5)$$

A higher support value indicates stronger appliance associations. The FP-Growth algorithm builds a compact FP-tree to extract frequent patterns efficiently. The Kulczynski (Kulc) measure evaluates association strength:

$$Kulc(A, B) = \frac{1}{2} \left(\frac{support(A \cap B)}{support(A)} + \frac{support(A \cap B)}{support(B)} \right) \quad (6)$$

This measure provides the conditional probability of appliance A operating given appliance B . Both the appliance-time (ΔH_{ki}) and γ are integrated to determine the controllability, $C_i(t)$, of an appliance i :

$$C_i(t) = \Delta H_{ki}(t) + \sum_{j=1}^n \gamma_j \Delta H_{kj}(t) \quad (7)$$

where $\Delta H_{kj}(t)$ represents the time variation in appliance-time association of appliances j . The flexibility of an appliance i is then quantified as:

$$F_i(t) = C_i(t) * \frac{P_i(t)}{f_i(t)} \quad (8)$$

where $f_i(t)$ represents the average daily usage cycles across various comfort zones and $P_i(t)$ is the active power of each appliance.

3.1.1. Ramp-rate flexibility

The flexibility quantification of thermostatically controlled appliances, such as heat pumps and HVAC systems, requires an intricate balance between user comfort, weather conditions, and inherent operational characteristics of appliances. A hybrid approach employing both K-means clustering and DBSCAN is introduced to characterize the flexibility of TCAs by integrating appliance-time and appliance-temperature associations. Ramp-rate flexibility refers to the ability of TCAs to increase or decrease energy consumption in response to external conditions.

K-means clustering is applied to consumption data to identify higher and lower comfort zones based on appliance-time associations. DBSCAN is then used within each cluster to analyze energy variations relative to external temperature, leveraging its ability to detect clusters of arbitrary shapes based on data density. This approach creates a temperature-energy landscape, revealing potential energy shifts within specific temperature ranges. DBSCAN is applied to the standardized data with specified epsilon (ϵ) and minimum samples ($min_samples$) parameters, which are crucial for determining the density threshold for cluster formation. The algorithm identifies high-density clusters, representing stable appliance operation with low power variability, and low-density clusters, reflecting significant temperature-driven fluctuations, often due to seasonal changes or unconventional usage.

These appliance-time and appliance-temperature associations provide ramp-rate flexibility to balance energy use and user comfort. Two key metrics are calculated for each DBSCAN cluster within the indicated temperature range: the peak power consumption P_{max} , and the standard deviation of the power consumption σ . The difference ΔP represents the amount of energy that can be provided for flexibility operations when the temperature lies in the specific range determined by the DBSCAN clustering.

$$\Delta P = P_{max} - |\sigma| \quad (9)$$

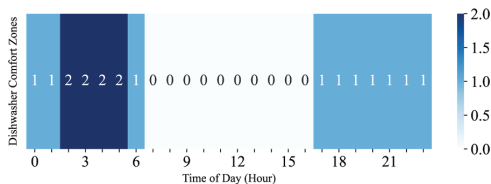


Fig. 2. Appliance to time association of shiftable appliances.

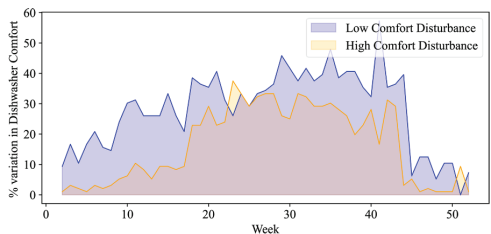


Fig. 3. Dynamic variation of dishwasher comfort zones across weeks.

Table 1
Statistical measures illustrating appliance usage associations.

Comfort	Appliance association		Kulc	$C_i(t)$	ΔH_{ki}	$F_i(t)$
High	Dishwasher	- Cloth dryer	3.9	3.87	3.5	0.620
		- Washing machine	3.2			
Low	Dishwasher	- Cloth dryer	0.8	16.48	8	1.680
		- Washing machine	0.2			

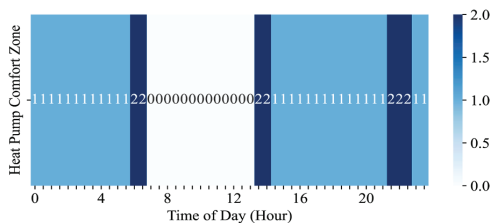


Fig. 4. Appliance to time association of a heat pump.

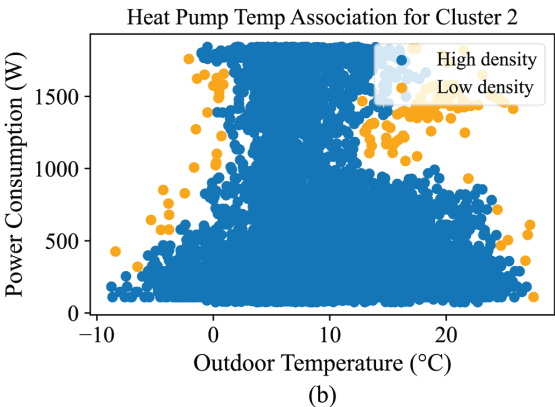
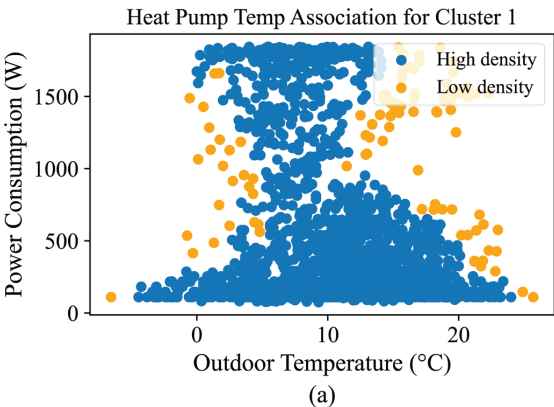


Fig. 5. Impact of outside temperature on heat pump power consumption for low (a) and high user comfort (b).

The ramp-rate flexibility, F_r , quantifies the rate of change in energy consumption under varying temperature conditions and is defined as:

$$F_r = \frac{\Delta P}{\Delta Temp \times \Delta t} \quad (10)$$

where $\Delta Temp$ represents the change in outdoor temperature between the same two consecutive data points and Δt is the flexibility provision duration.

3.1.2. Storage-dispatch flexibility

Battery energy storage systems enhance residential flexibility by storing and dispatching energy efficiently. Storage-dispatch flexibility refers to the available capacity within the battery SoC to support grid

Table 2
Ramp-rate flexibility under different temperature change scenarios.

Case	Comfort	$\Delta Temp$	Δt	σ	ΔP	F_r
Scenario 1	High	3	1	458.2	1353.88	451
	Low			425.2	1408.08	463
Scenario 2	High	4	2	458.2	1353.88	169
	Low			425.2	1408.08	176

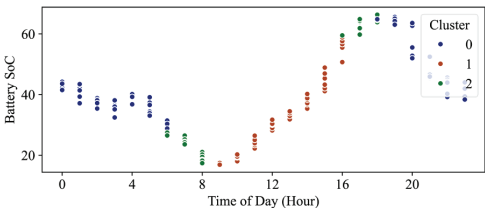


Fig. 6. Clustered battery usage and SoC patterns.

Table 3
Battery flexibility reserve metrics and SoC availability across clusters.

Battery utilization	Hour	V_k	α	F_{res}
High	20	2.88	1.93	2.38
	01		1.05	1.59
	04		0.58	1.11
Low	10	5.94	0.45	1.42
	12		0.60	1.51
	13		0.46	1.58

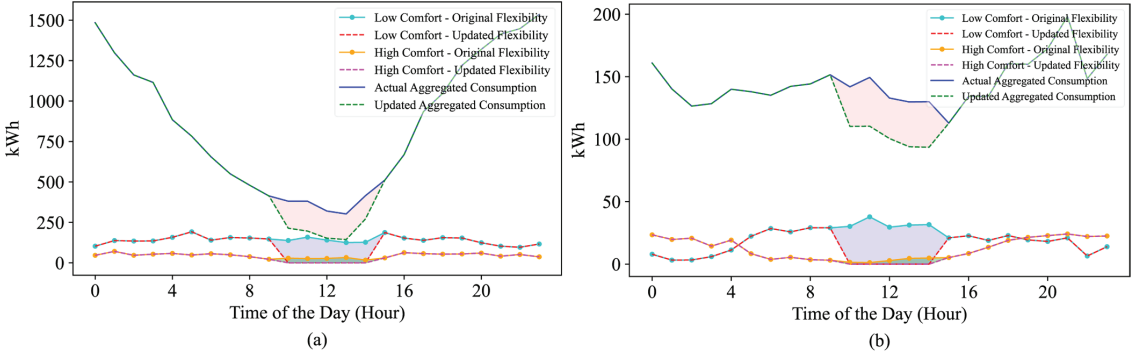


Fig. 7. Comparison of original and updated flexibility aggregation of heat pump (a) and BESS (b) during market bidding slot.

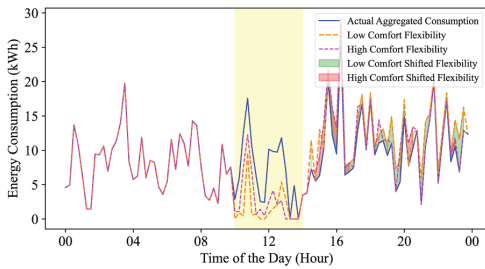


Fig. 8. Adjusted flexibility profiles for shiftable appliances during market bidding slot.

operations while maintaining operational limits. Key influencing factors include grid-supplied load, PV generation, SoC level, solar irradiance, charging/discharging rates, and temperature. Higher SoC offers greater flexibility, while lower SoC restricts adaptability.

To quantify flexibility, a dynamic time-series analysis categorizes battery operation into high and low utilization clusters. Multidimensional K-means clustering groups time periods with similar characteristics, analyzing SoC trends to determine flexibility reserves. Clusters with increasing SoC indicate available flexibility, whereas declining SoC signals constraints. The extent of SoC variability within each cluster, V_k , during high and low utilization periods in each cluster is calculated using:

$$V_k = \frac{(SoC_{c_max} - SoC_{c_min})}{\Delta T} \quad (11)$$

where SoC_{c_max} and SoC_{c_min} represent the maximum and minimum SoC in each cluster k , and ΔT is the cluster duration.

To capture hourly battery adaptability, the adaptability rate, the battery adaptability rate, α , is introduced:

$$\alpha = \frac{(SoC_{h_max} - SoC_{h_min})}{\Delta t_r} \quad (12)$$

where SoC_{h_max} and SoC_{h_min} represent the maximum and minimum SoC within each hour of a cluster, and Δt_r accounts for the number of timestamps. A high α score signifies a more dynamic response to load variations.

A flexibility reserve metric, F_{res} , is formulated in terms of battery variability and rate of adaptability. The F_{res} value estimates the battery capacity to supply energy for grid flexibility services. The flexibility of BESS for each cluster k is calculated as:

$$F_{res,k} = \frac{V_k * \alpha (SoC_{h_norm})}{\Delta t_r} \quad (13)$$

where SoC_{h_norm} is the normalized SoC. The metric is constrained to prevent excessive flexibility estimations, ensuring that rising SoC levels indicate increased flexibility potential while discharging phases limit flexibility. The initial flexibility reserve, F_{init} , provides a baseline assessment of BESS capacity:

$$F_{init} = SoC_{initial} - SoC_{h_min} \quad (14)$$

This framework offers a structured methodology for evaluating BESS flexibility and optimizing energy dispatch while ensuring stability in grid operations.

These quantified flexibility data serve as direct inputs to the aggregation and optimization framework. By capturing the inherent variability in user behavior and operational conditions, the model ensures that the aggregated flexibility remains adaptive to actual consumption patterns.

3.2. Flexibility aggregation

Flexibility aggregation in a residential energy community quantifies device-level flexibility for shiftable appliances, TCAs, and BESS, forming profiles for different comfort zones. A hierarchical model optimizes community-level flexibility using sequential MILP, ensuring market compliance while prioritizing lower comfort zone flexibility for symmetrical bidding and meeting minimum bid constraints.

The model considers a set of households $\mathcal{H}$, indexed by i , operating within a discrete hourly time intervals $\mathcal{T}$, indexed by t , and the set of appliance types $\mathcal{A}$, indexed by a . The flexibility available from appliance a in household i during hour t for the lower and higher comfort zones is denoted as $P_{i,a,t}^{low}$ and $P_{i,a,t}^{high}$, respectively. To prioritize $P_{i,a,t}^{low}$, a sequential optimization approach is adopted, where the first stage maximizes the utilization of $P_{i,a,t}^{low}$, while the second stage optimizes $P_{i,a,t}^{high}$ after fully utilizing the lower comfort zone. The binary decision variables $U_{i,a,t}^{up}$ and $U_{i,a,t}^{down}$ indicate whether a specific appliance provides up-regulation or down-regulation at a given time. The aggregated up-regulation and down-regulation flexibility at time t are represented by $P^{up}(t)$ and $P^{down}(t)$, with the objective function formulated as:

$$\min \sum_{i \in \mathcal{H}} \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} (P_{i,a,t}^{low} + P_{i,a,t}^{high}) \quad (15)$$

$$s.t \ P^{up}(t) = P^{down}(t), \forall t \in \mathcal{T} \quad (15a)$$

$$P^{up}(t) \geq P_{min}(1 + \beta), \forall t \in \mathcal{T} \quad (15b)$$

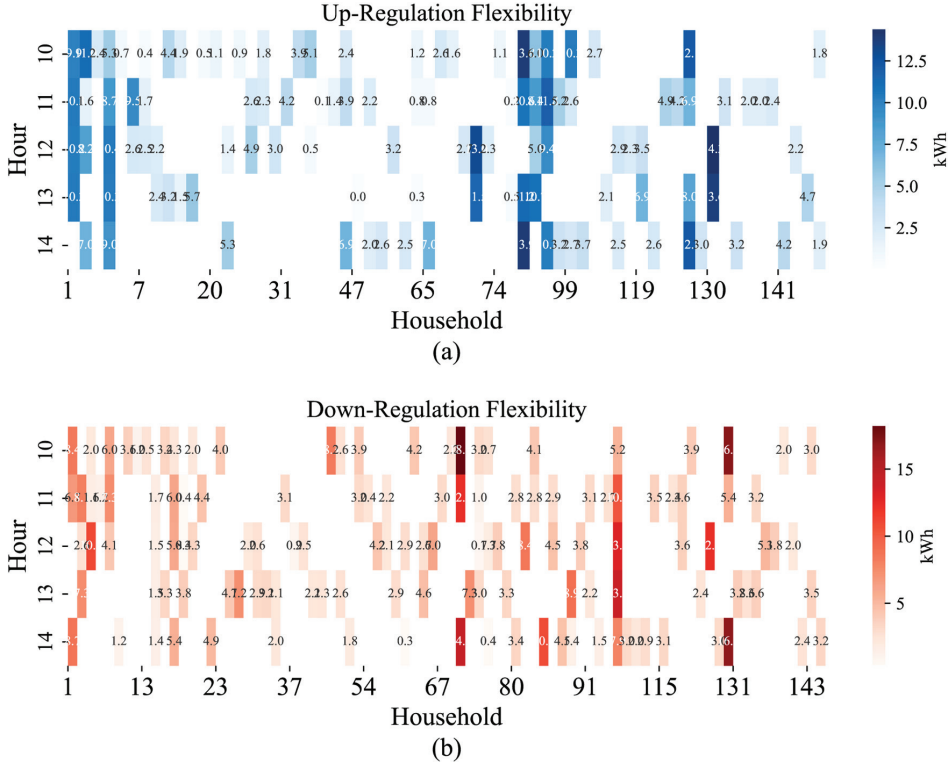


Fig. 9. Distribution of up-regulation (a) and down-regulation (b) flexibility across different households.

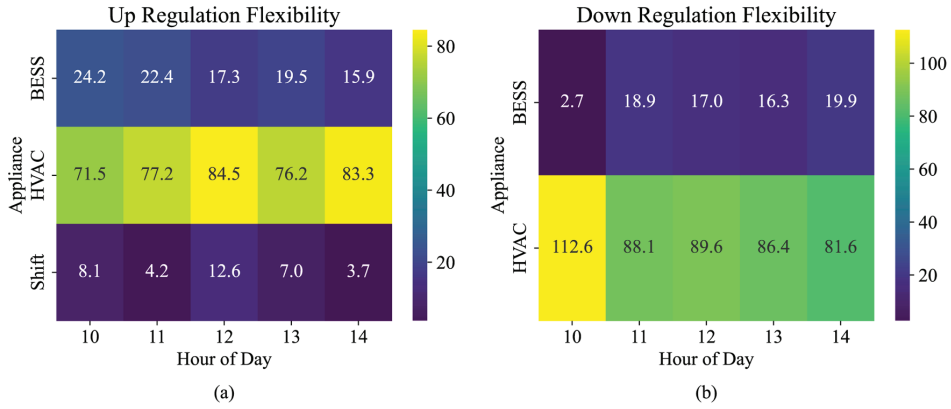


Fig. 10. Distribution of up-regulation (a) and down-regulation (b) flexibility provided by different appliance types.

$$P^{\text{down}}(t) \geq P_{\min}(1+\beta), \forall t \in \mathcal{T} \quad (15c)$$

$$U_{i,a,t}^{\text{up}} + U_{i,a,t}^{\text{down}} \leq 1, \forall i \in \mathcal{H}, a \in \mathcal{A}_{\text{HVAC}}, t \in \mathcal{T} \quad (15d)$$

$$U_{i,a,t}^{\text{up}} + U_{i,a,t+1}^{\text{up}} \leq 1, \forall i \in \mathcal{H}, a \in \mathcal{A}_{\text{TCA}}, t+1 \in \mathcal{T} \quad (15e)$$

$$U_{i,a,t}^{\text{down}} + U_{i,a,t+1}^{\text{down}} \leq 1, \forall i \in \mathcal{H}, a \in \mathcal{A}_{\text{TCA}}, t+1 \in \mathcal{T} \quad (15f)$$

$$U_{i,a,t}^{\text{up}} = 0, \text{ if } \text{SoC} \leq 45, \forall i \in \mathcal{H}, a \in \mathcal{A}_{\text{BESS}}, t \in \mathcal{T} \quad (15g15)$$

The up-regulation and down-regulation capacities at any time t are determined by the aggregated flexibility provided by all appliances in all households, given by:

$$P^{\text{up}} = \sum_{i \in \mathcal{H}} \sum_{a \in \mathcal{A}} \left(U_{i,a,t}^{\text{up}} \left(P_{i,a,t}^{\text{low}} + P_{i,a,t}^{\text{high}} \right) \right) \quad (16)$$

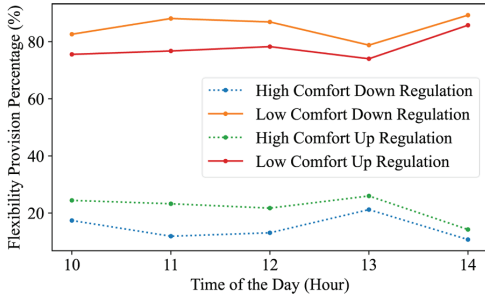


Fig. 11. Flexibility provision proportions by comfort zone during market bidding slot.

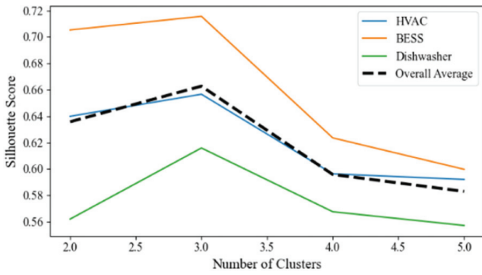


Fig. 12. Clustering validation across different appliance types.

Table 4
Comparison of flexibility aggregation optimization performance.

Strategies	Scalability	Variables	Constraints	Computational time
Heuristics (PSO)	150 houses $\times$ 4 appliances (4 h slots)	18,023	12,600	23.37 s
Proposed				2.20 s
Heuristics (PSO)	1000 houses $\times$ 4 appliances (4 h slots)	120,067	84,000	154.28 s
Proposed				7.40 s

$$p^{\text{down}} = \sum_{i \in \mathcal{H}} \sum_{a \in \mathcal{A}} \left(U_{i,a,t}^{\text{down}} \left(p_{i,a,t}^{\text{low}} + p_{i,a,t}^{\text{high}} \right) \right) \quad (17)$$

Expression 15a introduces symmetrical bids, regardless of the possibility of offering asymmetrical quantities within the bidding slot. Thus, assists in managing rebounds as well. Constraints (15b) and (15c) establish a minimum bid threshold, $P_{\min}$, adjusted by a buffer percentage β , to avoid penalties. Expressions (15d) and (15e) regulate TCA operations, preventing consecutive activations, while expression (15f) restricts the same appliances from providing simultaneous up and down-regulation. Constraint (15g) ensures safe BESS operation by preventing excessive discharge.

4. Case study

This section demonstrates the proposed flexibility quantification and aggregation methodology through two case studies, developed in the context of participation in Fingrid's Frequency Containment Reserve for Normal Operation (FCR-N) market, which requires symmetrical bidding and compliance with strict technical standards. The first case study uses AMPDs and Cornwall LEM datasets, where shiftable and thermostatically controlled appliances are sourced from AMPDs, while solar PV and battery storage data come from Cornwall LEM. One year of high-

resolution data is aggregated into 30-minute intervals, extracting key temporal and energy features to build a behavioral transactional database. The second case study aggregates flexibility across 150 households using Pecan Street data. Preprocessing includes missing value imputation, outlier removal, and standardization, with data synchronized into 1-hour intervals for analysis.

K-means clustering is applied with $n_{\text{init}} = 5$ and $\text{max_iter} = 300$, with the number of clusters selected using silhouette analysis. FP-Growth is tuned with a minimum support of 0.1 and confidence threshold of 0.8. DBSCAN uses $\text{eps} = 0.7$ and $\text{min_samples} = 5$, tuned through empirical evaluation. The sequential MILP model is solved using Gurobi with a 0.1 % optimality gap. All simulations are performed on a system with an Intel Core i7 processor and 64 GB RAM.

4.1. Case study 1: flexibility potential of an individual household

The flexibility potential of an individual household is determined on a day-ahead basis, utilizing one year of historical data for model training. Subsequently, the data from the most recent day is employed to conduct the quantification assessment to ensure past usage behaviors.

4.1.1. Demand-shift flexibility analysis

This case study characterizes the available flexibility of three shiftable appliances: washing machine, clothes dryer, and dishwasher, with power ratings of 250 W, 4700 W, and 770 W, respectively. Dishwasher data is used for detailed analysis. The process starts with mapping out appliance-time associations. K-means clustering identifies lower and higher comfort zones for each appliance, as shown in Fig. 2. The dynamic behavior of a customer regarding dishwasher usage over the weeks is shown in Fig. 3.

Appliance-appliance association is evaluated by applying the FP-Growth algorithm to identify frequent appliance usage patterns. Conditional probabilities and the Kulc measure are used to quantify appliance associations, while appliance controllability is incorporated to compute flexibility, as shown in Table 1.

4.1.2. Ramp-rate flexibility analysis

Fig. 4 highlights user comfort zones regarding heat pump usage. The influence of external temperature on heat pump power consumption is assessed by applying DBSCAN, as illustrated in Fig. 5. Following this, the maximum power, $P_{\max}$ and standard deviation, σ , for each DBSCAN cluster under normal operating conditions are computed for ΔP .

Ramp-rate flexibility is characterized under two distinct scenarios during standard operating conditions: Firstly, when flexibility is needed for one hour with an anticipated outside temperature change of 3 °C, and secondly, when flexibility is required for two hours with an outside temperature change of 4 °C. Table 2 summarizes the ramp-rate flexibility of the heat pump under these scenarios.

From the flexibility analysis of the heat pump, it is observed that R_r has a strong relation with user comfort in the sense that with the increase in flexibility duration or with a greater change in outside temperature, R_r tends to decrease to keep the comfort level of the user intact.

4.1.3. Storage dispatch flexibility analysis

Multidimensional K-means clustering identifies daily battery SoC patterns using outdoor temperature, solar irradiance, and grid-PV contribution. Fig. 6 shows the correlation between battery SoC and comfort clusters, highlighting charging during daylight and discharging in high comfort zones, aiding in understanding user battery usage patterns and charged/discharged periods. By examining the battery usage trends and SoC dynamics, the battery variability V_k and hourly adaptability rate α are used to calculate flexibility reserve in each cluster, as shown in Table 3. It is observed that during periods of low utilization (cluster 1), the battery has a higher availability of SoC to provide flexibility services. This is attributed to the battery being charged by the solar PV system and the high variability.

By examining the battery usage trends and SoC dynamics, the battery variability, V_k , and hourly adaptability rate, α , the flexibility reserve is measured in each cluster, as shown in Table 3. It is observed that during periods of low utilization (cluster 1), the battery has a higher availability of SoC to provide flexibility services. This is attributed to the battery being charged by the solar PV system and the high variability.

4.2. Case study 2: flexibility aggregation

After quantifying the flexibility, the aggregation process is performed separately for each appliance type within the households under different comfort zones. For efficient participation in the balancing market for FCR services, a specific 4-hour window from 10:00 to 14:00 is selected, and the maximum available flexibility is evaluated for up-regulation regarding each appliance type for demonstration. Fig. 7 shows how the actual aggregated consumption of the heat pump and BESS is adjusted within the 4-hour window, reflecting the up-regulation flexibility that can be utilized. The solid green and pink shaded areas in Fig. 8 highlight the demand shift flexibility. The results clearly illustrate how the consumption of shiftable appliances is redistributed across the day, leading to noticeable load concentrations in the hours following the market bidding window. This behavior offers a preliminary indication of the rebound effect, particularly for appliances such as electric vehicles, dishwashers, and dryers, whose operation is delayed and then resumed in time periods later in the day.

Following the aggregation, the MILP model is applied to optimize the dispatch of this flexibility. The sequential optimization process aimed to disaggregate flexibility among households and appliances to provide symmetrical up-regulation and down-regulation while minimizing user discomfort. Fig. 9 shows the distribution of up-regulation and down-regulation flexibility across various households during the 10:00 to 14:00 market bidding slot.

To elaborate on the total up-regulation and down-regulation flexibility provided by each appliance type, Fig. 10 shows aggregated appliance-specific flexibility contributions. Fig. 11 highlights the flexibility provision percentage across both comfort zones over the 4-hour period. The low comfort zone, where user comfort is slightly compromised, provides a higher percentage of up-regulation flexibility, averaging around 77–80 %, while the high comfort zone's contribution remains around 23 %. Similarly, for down-regulation, the average flexibility provision across high and low comfort zones is 85 % and 15 %, respectively.

The effectiveness of the proposed methodology is evaluated through two key analyses: clustering performance and optimization scalability. To validate the dynamic comfort zone classification, silhouette score analysis is performed for different numbers of clusters across multiple appliances, including HVAC, BESS, and dishwashers. As shown in Fig. 12, the silhouette scores peaked consistently around 3 clusters, confirming the appropriateness of our comfort zone structure. In terms of optimization, we benchmarked our sequential MILP approach against Particle Swarm Optimization (PSO) to assess scalability. As seen in Table 4, the proposed strategy significantly outperformed PSO both in terms of speed and scalability.

However, clustering quality depends on appropriate historical data length as poor clustering could misclassify comfort zones. Additionally, while the MILP model is highly efficient, it assumes pre-computed flexibility values and does not yet incorporate real-time updates under uncertainty, which is a direction for future work. The proposed flexibility quantification and aggregation methodology allows aggregators to effectively optimize flexible energy resources for market participation while maintaining dynamic user comfort.

5. Conclusion and future work

This study proposes a data-driven methodology to quantify and aggregate demand-side flexibility, addressing the critical challenges of

dynamic user behavior towards appliance usage and symmetrical flexibility provision of balancing market participation. The methodology integrates machine learning techniques to quantify demand-shift, ramp-rate, and storage-dispatch flexibility at the appliance level. These flexibilities are aggregated through a hierarchical framework and optimized using sequential MILP to ensure compliance with market participation constraints with minimum user discomfort.

- For individual households, shiftable appliances provided a flexibility of 12.36 kWh flexibility in low comfort zones. Heat pumps offered ramp-rate flexibility of 463 W/hr for a 3 °C temperature shift, and BESS achieved a higher variability of 5.94 % during low utilization periods.
- The aggregated flexibility from 150 households demonstrated substantial grid contributions, achieving 85 % down-regulation flexibility and 77–80 % up-regulation flexibility from the low comfort zone, during critical 4-hour market bidding slots.
- Furthermore, our sequential MILP model exhibits excellent computational efficiency and scalability, with optimization times of only 0.20 s for 150 households and 1.40 s for 1000 households, in stark contrast to heuristic approaches.

Future work will focus on incorporating rebound effects into the flexibility aggregation model and evaluating their implications on grid operations. Additionally, real-time digital simulation (RTDS) will be utilized to validate the performance of the proposed strategies under dynamic grid conditions.

CRedit authorship contribution statement

Arqum Shahid: Methodology, Formal analysis, Data curation, Conceptualization. **Roya Ahmadihangar:** Supervision, Methodology, Investigation. **Jako Kilter:** Writing – review & editing, Validation. **Argo Rosin:** Visualization, Supervision, Conceptualization.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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Appendix 4

Publication IV

A. Shahid, R. Ahmadiyahangar, T. Korötko, and A. Rosin, "Transfer Learning-Based Aggregated Flexibility Forecasting for Participation in Local Energy Markets," IEEE International Conference on Communication, Computing, Networking, and Control in Cyber-Physical Systems (CCNCPS), pp. 69–73, Jun. 2025, doi: 10.1109/ccncps66785.2025.11135603.

Transfer Learning-Based Aggregated Flexibility Forecasting for Participation in Local Energy Markets

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Abstract—Increasing renewable integration positions energy aggregators as key entities in local energy markets. However, the complexity of accurately forecasting the aggregated flexibility of individual households within the aggregator portfolio and subsequently real-time decision-making based on market bidding, limits ancillary services provision. This paper proposes a novel transfer learning-based forecasting framework using XGBoost to estimate aggregated flexibility in energy communities by leveraging appliance-level data. The methodology involves a multi-stage pipeline beginning with variance-aware feature extraction using principal component analysis for early household selection, followed by clustering to capture diverse consumption and flexibility patterns for identifying representative households. Appliance-level consumption and flexibility data from these households are used to train a base XGBoost model. The learned knowledge from this model is then transferred and fine-tuned using aggregated data to generalize flexibility forecasting across the entire community, reducing training overhead while maintaining accuracy. The results demonstrate the effectiveness of the proposed methodology by exhibiting the average RMSE of 4.46 kW and R^2 of 0.67. These outcomes support the effective participation of aggregators in local energy markets.

Keywords—energy flexibility, energy markets, flexibility aggregation, machine learning

I. INTRODUCTION

The global transition toward renewable energy systems has fundamentally reshaped electricity markets, necessitating decentralized frameworks to accommodate variable generation from solar, wind, and other distributed resources. Within this paradigm, energy aggregators have emerged as key intermediaries, enabling the collective participation of residential prosumers in local energy markets (LEMs) [1]. By pooling the flexibility of distributed energy resources (DERs) such as rooftop solar, batteries, and controllable loads, aggregators can provide ancillary services, balance supply-demand mismatches, and optimize market revenues [2].

As LEMs evolve, the ability of aggregators to act on behalf of prosumers depends heavily on their capacity to monitor, forecast, and control the aggregated flexibility of their portfolio. This aggregated flexibility is inherently dynamic and highly sensitive to user behavior, device-level characteristics, weather conditions, and tariff structures [3].

Forecasting this flexibility in a timely and accurate manner is crucial not only for ensuring operational efficiency and grid stability but also for enabling strategic bidding in LEMs.

However, accurately forecasting aggregated flexibility remains a complex task. The diverse nature of residential energy consumption shaped by varying appliance usage, user behavior, and DER configurations, makes it difficult to develop a unified forecasting model that generalizes well across all households [4], [5]. Models trained on one subset of homes often fail to capture the variability present in others, leading to poor scalability and reduced accuracy. Additionally, the computational burden of processing appliance-level data from thousands of devices poses significant challenges, especially in real-time settings where rapid decision-making is essential for market bidding. These complexities are further compounded by data sparsity and inconsistency across households, making it difficult for aggregators to implement robust and efficient forecasting solutions [6].

Recent studies have explored various methodologies to enhance flexibility forecasting. In [7], GRU-based architectures for industrial load forecasting achieved a 20% reduction in MAE by leveraging time-series production and weather data. Hybrid deep learning frameworks combining convolutional LSTMs with residual load decomposition demonstrated high accuracy in forecasting power system flexibility requirements at regional scales [8]. A hybrid top-down model combining probabilistic estimation forecasts demand-side flexibility using a virtual battery approach, achieving MAPE below 17% during DR events [9], [10]. Accurate building- and aggregated-level forecasting using random forest is shown to be critical in smart grid flexibility markets, with MAPE ranging from 10.77% to 31.52% [11]. Additionally, ML-based frameworks leveraging XGBoost and k-means clustering have demonstrated strong performance in forecasting next-day residential flexibility while incorporating dynamic consumer behavior [12]. A federated learning-based feedforward neural network approach has been introduced to forecast hot water demand for flexibility aggregation while preserving user privacy [13]. Similarly, In [14], limited users and smart meter data are utilized to forecast aggregated demand flexibility by using a feed-forward artificial neural

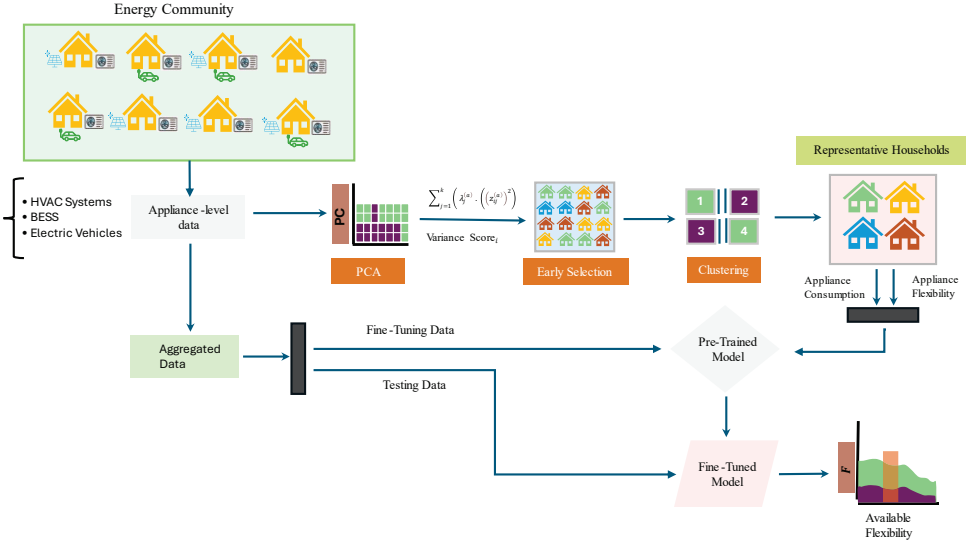


Fig. 1. Transfer learning-based framework for community-level aggregated flexibility forecasting

network. While existing studies demonstrate progress in flexibility forecasting, most studies lack consideration of detailed device-level insights with community-wide generalizability for flexibility aggregation. Furthermore, the computational demands of processing high-resolution data from numerous appliances pose scalability challenges, particularly for real-time market bidding. This paper addresses these challenges through a novel transfer learning (TL)-based framework designed to forecast aggregated flexibility within energy communities by leveraging models trained on a subset of houses by using only the community-level load data and without needing to forecast each house individually.

II. METHODOLOGY

Fig. 1 illustrates the methodology adopted to forecast aggregated appliance-level flexibility within a residential energy community using a transfer learning approach. The methodology involves three phases: appliance-level flexibility quantification, representative house selection via variance-aware PCA and clustering approach, and transfer learning-based forecasting using XGBoost.

A. Appliance-Level Flexibility Quantification

The first phase involves determining the flexibility potential of individual appliances across each household. This study focuses on three key flexible resources: HVAC systems, Battery Energy Storage Systems (BESS), and shiftable appliances (e.g., dishwashers, washing machines). This study adopts the appliance-level flexibility quantification methodology proposed in our prior work [12], where demand-side flexibility is evaluated by analyzing the operational behavior of individual household appliances.

For shiftable appliances, flexibility is quantified by identifying the potential time windows in which appliance operations can be shifted, using binary operation states and historical activation patterns.

$$F_{s,a}(c) = P(T_c - O_d(c)) \quad (1)$$

For thermostatically controlled appliances, flexibility is assessed by analyzing variations in energy consumption under changing environmental conditions. The quantification involves computing the difference between the allowable operating window and the actual usage duration to estimate the available flexibility.

$$F_T(t) = \bar{E}(t)(1 - \sigma) \left(1 + \frac{E_{std}(t)}{\bar{E}(t)} \right) Temp_f(t) \quad (2)$$

For BESS, flexibility is defined as the available energy that can be charged or discharged within operational constraints. The instantaneous flexibility is calculated as the product of the available power margin and the allowable activation duration within the SoC boundaries.

$$F_{BESS}(t) = \min \left(P_{max}, \frac{E_{avail}(t)}{\Delta t} \right) \quad (3)$$

The quantified flexibility for each appliance type across all representative households serves as the input for the representative house selection and forecasting model development.

B. Representative Household Selection

The second phase identifies a subset of households whose flexibility patterns are most representative of the entire community. For each appliance type, time-series data is processed into a structured feature matrix, where each row corresponds to a household, and columns include statistical features such as mean, max, min, standard deviation, and peak-to-average ratio, and temporal patterns such as time of the day, average load in peak hours, and off-peak hours.

The resulting matrix $X^{(a)} \in R^{n \times m}$ is constructed separately for each appliance type a , with n and m correspond number of households and features.

To reduce dimensionality and determine initial selected group of households, while retaining core load behavior characteristics, principal component analysis is applied

individually on each appliance's feature matrix $X^{(a)}$. The principal components (PCs) capture uncorrelated directions of maximum variance:

$$Z^{(a)} = X^{(a)} \cdot W^{(a)} \quad (4)$$

where, $Z^{(a)}$ and $W^{(a)}$ correspond transformed data in PC space and matrix of eigenvectors (principal components) sorted by their corresponding eigenvalues in descending order, such that the first few PCs retain the majority of variance present in $X^{(a)}$.

To quantify the contribution of each household to the total variance captured by the retained components, a household variance score $V_i^{(a)}$ is computed for each house i as:

$$V_i^{(a)} = \sum_{j=1}^k (\lambda_j^{(a)} \cdot ((z_{ij}^{(a)})^2)) \quad (5)$$

where, $\lambda_j^{(a)}$ is the eigenvalue corresponding to the j^{th} PC of appliance a , and $z_{ij}^{(a)}$ is the projection of household i on the j^{th} PC. k is chosen such that the cumulative explained variance exceeds a threshold such as 90%.

Houses with the highest variance scores are considered early representatives, as they span the major directions of variation within the community's appliance-specific load behavior. To ensure that the selected houses are not biased toward a single energy usage pattern, K-means clustering is applied on the projected PC space $Z^{(a)}$. This groups households into K clusters based on appliance usage similarity. From each cluster, representative houses closest to the cluster centroid are selected to maintain pattern diversity in the training set. This ensures the transfer learning model captures heterogeneous behavioral patterns. The clustering process is formalized as:

$$\min_c \sum_{j=1}^K \sum_{i \in C_j} \|z_i^{(a)} - \sigma_j\| \quad (6)$$

where, C_j is the set of household indices and σ_j is the centroid of cluster j . The aggregated individual appliance load data of these representative households are used to forecast community-level flexibility using transfer learning.

C. Transfer Learning-Based Flexibility Forecasting

After selecting the representative households for each appliance type using the PCA-variance and clustering strategy, a transfer learning framework is employed to scale the forecasting model from the subset of houses to the entire community. The goal is to predict the total community-level flexibility for each appliance using only the aggregated load data, while leveraging the patterns learned from smaller representative households.

Let $D_s^{(a)} = \{X_s^{(a)}, Y_s^{(a)}\}$ denote the source domain for appliance $a \in \{HVAC, BESS, Shiftable\}$, where $X_s^{(a)} \in R^{T \times d}$ denotes feature matrix including time-series appliance loads and contextual features for the selected representative households over time T and $Y_s^{(a)} \in R^T$ corresponds to flexibility time series calculated using (1-3) for each appliance type. An XGBoost model is trained on this source domain to learn the nonlinear mapping. XGBoost is employed for its robust ability to capture complex nonlinear relationships and interactions in high-dimensional, time-series data.

$$f_{\theta_s^{(a)}}: X_s^{(a)} \rightarrow Y_s^{(a)} \quad (7)$$

where, $\theta_s^{(a)}$ represents the learned parameters of the model trained on the representative houses for appliance a .

To scale this model to the target domain $D_T^{(a)} = \{X_T^{(a)}\}$, where $X_T^{(a)}$ denotes the aggregated community-level load data for appliance a , we adapt the pre-trained model using transfer learning, defined as:

$$f_{\theta_T^{(a)}}(X_T^{(a)}) = f_{\theta_s^{(a)}}^{TL}(X_T^{(a)}) \quad (8)$$

Here, $f_{\theta_s^{(a)}}^{TL}$ is the transfer-adapted model applied directly to the community-level load features. The model generalizes flexibility behavior by leveraging the nonlinear mappings captured during pretraining, without requiring flexibility labels from the full community.

III. RESULTS AND DISCUSSION

The proposed transfer learning-based forecasting framework is evaluated using appliance-level flexibility data from the Pecan Street and Cornwall LEM datasets, aggregated over 15-minute intervals. The aggregator's portfolio consists of 400 HVAC systems, 100 BESS units, and 50 dishwashers. Representative households were selected using a variance-aware PCA-clustering method, and appliance-level transfer learning models were trained using XGBoost to generalize to community-level flexibility forecasting without individual house-level predictions. To ensure robust performance, hyperparameter optimization is performed using a grid search strategy. The key XGBoost parameters optimized included: maximum tree depth $\in \{3, 5, 7\}$, learning rate $\in \{0.01, 0.05, 0.1\}$, number of estimators $\in \{100, 300, 500\}$, and subsample ratio $\in \{0.6, 0.8, 1.0\}$. Each parameter combination was evaluated using 5-fold time-series cross-validation. The best-performing configuration was max_depth=5, learning_rate=0.05, n_estimators=300, and subsample=0.8 for the pre-trained model. Flexibility for each appliance is computed based on dynamic device models using (1-3).

Fig. 2 illustrates the comparison between the actual and predicted aggregated flexibility for the BESS component. Similarly, Fig. 3 presents the forecasting results for dishwasher flexibility. Despite the inherent variability and user-driven nature of shiftable appliance usage, the model demonstrates a reasonable ability to anticipate aggregated flexibility patterns. Fig. 4 displays predicted versus actual aggregated HVAC flexibility. Given the cyclic and thermally driven operation of HVAC systems, the model performs strongly, with high predictive accuracy and consistency across the time series.

Cluster-wise contribution analysis shown in Fig. 5-7 highlights how the transfer learning framework retained appliance diversity from representative households when scaling to community-level predictions. For BESS, six distinct clusters contributed to the aggregated forecast, revealing diverse usage patterns across representative households. The dishwasher flexibility derived from five clusters highlights varying operational schedules and user behaviors, explaining the moderate predictive challenges.

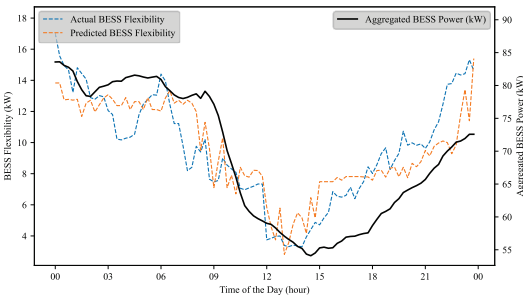


Fig. 2. Comparison of actual and predicted BESS flexibility

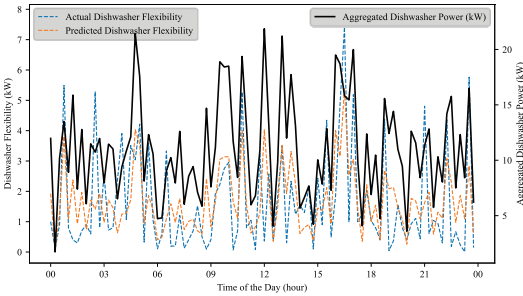


Fig. 3. Comparison of actual and predicted Dishwasher flexibility

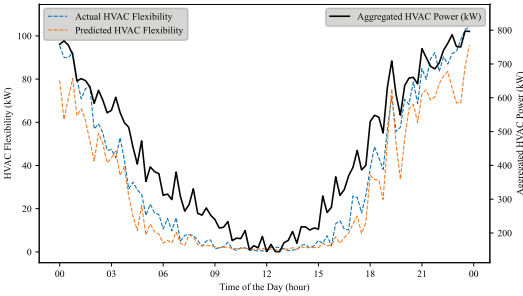


Fig. 4. Comparison of actual and predicted HVAC flexibility

HVAC flexibility, derived from ten clusters, shows a wide range of operational patterns reflecting diverse residential thermal management preferences and behaviors. These cluster-wise analyses contribute to effective aggregator-level forecasting.

Table I provides a quantitative summary of transfer learning model performance across appliance categories. The HVAC model achieved the highest accuracy with an R^2 value of 0.91, highlighting the strength of the transfer learning framework in capturing temporally consistent and high-frequency loads. The BESS model also performed satisfactorily with an R^2 of 0.74 and a low RMSE of 1.78 kW. However, dishwasher flexibility prediction yielded a lower R^2 of 0.36, reflecting the irregularity and lower granularity of usage patterns in such appliances.

The average R^2 of 0.67 across all appliance types indicates the viability of the proposed methodology in forecasting

aggregated community flexibility with a reasonable trade-off between scalability and accuracy.

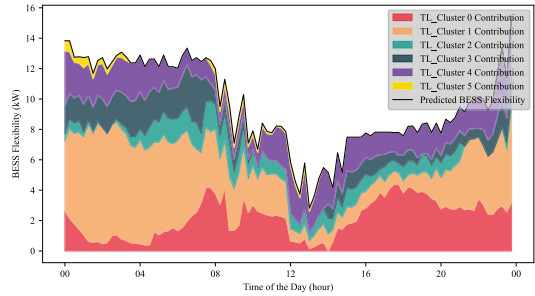


Fig. 5. Predicted BESS flexibility with cluster-wise contributions using transfer learning from representative households.

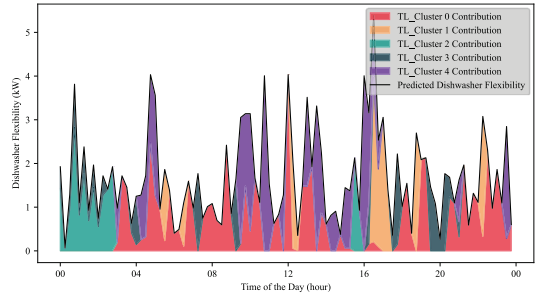


Fig. 6. Predicted dishwasher flexibility with cluster-wise contributions using transfer learning from representative households.

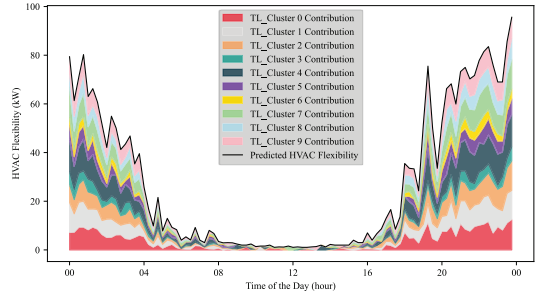


Fig. 7. Predicted HVAC flexibility with cluster-wise contributions using transfer learning from representative households.

TABLE I. MODEL PERFORMANCE COMPARISON ACROSS PREDICTED VS ACTUAL AGGREGATED FLEXIBILITY.

Appliance Type	Cluster Contribution	RMSE (kW)	R^2
HVAC	10	10.29	0.91
BESS	6	1.78	0.74
Dishwasher	5	1.32	0.36
Average	4.46		0.67

These results validate the efficacy of using transfer learning by eliminating the need for per-house training or real-time appliance-level monitoring across the full portfolio, offering a computationally efficient and generalizable solution for aggregators operating in local energy markets.

IV. CONCLUSION

This study presents a novel and scalable transfer learning-based framework for forecasting community-level aggregated flexibility by leveraging representative household data and appliance-level insights. By integrating a variance-aware PCA and clustering approach for representative selection with XGBoost-based transfer learning, the proposed methodology effectively predicts aggregated flexibility for key residential resources—HVAC systems, BESS, and shiftable appliances—without requiring individualized models for every household. The model demonstrated strong performance, particularly for HVAC and BESS systems, achieving high predictive accuracy. However, forecasting accuracy for low-duty-cycle, user-initiated shiftable appliances (dishwashers) remains modest, due to the sparsity of activation events and lack of behavioral pattern in their usage. The results highlight the potential of representative learning and transfer-based forecasting in enabling energy aggregators to make timely and informed decisions for market bidding and grid service provisioning.

Future work will focus on integrating real-time adaptive learning to enhance forecasting accuracy under evolving user behavior and environmental conditions. A systematic benchmark against baseline methods will be conducted to quantify the relative performance gains achieved by the proposed transfer-learning framework. Additionally, incorporating privacy-preserving techniques and extending the framework to include emerging flexible assets like EVs will be explored.

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Appendix 5

Publication V

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Forecasting Demand-side Flexibility of a Household with Dynamic Consumer Behavior Analysis

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Abstract— Demand-side flexibility is considered an efficient concept for enhancing grid stability and optimizing energy resources amidst increasing renewable energy integration and fluctuating consumption patterns. A challenging task in demand-side flexibility adaptation is to forecast its availability while considering consumer comfort to assist aggregators in efficient energy management. This paper proposes a novel machine learning-based approach to address this issue by quantifying the demand side flexibility of household appliances and utilizes this quantification to forecast next-day flexibility, incorporating dynamic consumer behavior analysis. To achieve this, various flexibility metrics are employed, and temporal and energy variations are analyzed across flexible appliances, enabling a better comprehension of their interaction with the environment. K-means clustering is used to analyze consumer behavior, and XG-Boost is applied to forecast flexibility. Accurate forecasting of the flexibility profile is required to avoid penalties for not meeting the contracted capacity and to minimize the risk of failing to provide flexibility reserve due to overestimation of production by the aggregator. The results show that the proposed approach can be used to forecast flexibility with high accuracy.

Keywords—demand side flexibility, smart appliances, user comfort, forecasting, quantification

I. INTRODUCTION

The power sector is increasingly sensitive to the load profiles of emerging utilities as the growing adoption of solar and wind energy introduces challenges associated with their intermittent nature [1]. This shift towards renewable energy systems necessitates demand-side flexibility, which is provided by innovative demand-side technologies. Accurate quantification and forecasting of this flexibility are essential for the sustainability of modern power systems [2]. Particularly, the residential sector, which accounts for a substantial share of energy consumption in most countries, presents cost-effective opportunities for energy management with minimal investment requirements. For instance, in the United States, a mere 5% reduction in load during the top 1% of peak hours could yield annual savings of approximately \$3 billion through targeted demand-side management (DSM) techniques [3].

In the residential sector, quantifying demand-side flexibility involves determining the flexibility potential of various consumer-related controllable resources [4]. These include shiftable appliances, thermostatically controlled loads, and battery energy storage systems. Understanding the technical characteristics of these appliances and consumer behavior toward energy consumption is crucial for this assessment [5]. For instance, shiftable appliances, which

consume a certain amount of energy within a given timeframe, offer flexibility by shifting their operating schedules. The flexibility of thermostatically controlled appliances (TCA) depends on the system's natural inertia and can be provided by adjusting temperature setpoints or power consumption [6]. This dispatchable flexibility asset can be traded by the consumer through aggregators in different energy markets such as day-ahead, intra-day, and ancillary services [7].

The increasing influx of data from residential smart meters presents both energy providers and consumers with a unique opportunity to identify and analyze consumer energy consumption behavior for flexibility services provision. Machine learning plays a significant role in this context by utilizing predictive analytics to understand energy usage patterns, clustering techniques for behavioral segmentation, and optimization algorithms for efficient energy management, all while adapting to evolving data and changing environmental conditions [8]. In this paper, a machine learning-based flexibility quantification and forecasting model is designed for shiftable appliances and TCAs by considering dynamic consumer comfort. K-means clustering is employed to analyze consumer behavior towards appliance usage by categorizing comfort into low and high levels, while the XG-Boost algorithm is utilized for flexibility forecasting, considering environmental conditions.

II. LITERATURE REVIEW

In order to manage the increasing energy demand while taking into account the intermittent nature of renewable energy generation, the literature is focused on DSM techniques. In [9], a Minibatch X-mean clustering-based flexibility quantifies flexibility as a function of mean power and controllability after extracting the state of each appliance. In [10], energy flexibility is characterized based on the appliance power value distribution and starting time distribution. XG-Boost is utilized to extract the consumption pattern of shiftable appliances. By utilizing LSTM, [11] quantifies and forecasts the flexibility of virtual power plants by considering the previous operating states without considering consumer comfort. Similarly, the decision-based building thermal flexibility model is designed by considering the demand response events as a baseline [12]. In [13], limited users and smart meter data are utilized to forecast aggregated demand flexibility by using a feed-forward artificial neural network (ANN). User behavior characterization is incorporated in the development of a home energy management system by considering ANN-based NILM techniques [14]. In the literature, the flexibility of appliances is mostly characterized and quantified by identifying two

distinct energy curves that bind the regular operation of the appliances without considering continuously varying consumer behavior toward appliance usage. In this paper, these challenges are overcome by developing a comprehensive flexibility quantification and forecasting approach.

III. METHODOLOGY

This study develops a comprehensive methodology to forecast the demand-side flexibility of a household by quantifying the flexibility of shiftable appliances and thermostatically controlled appliances (TCA). In this approach, historical data analysis is integrated with predictive modeling to dynamically assess the flexibility potential of these systems under varying operational and environmental conditions.

A. Data Preprocessing

The data, primarily consisting of operational metrics from shiftable appliances and TCA undergoes thorough cleaning, imputation of missing values, removing outliers, and temporal transformation. These records are supplemented by corresponding outdoor temperature measurements and user-defined operation schedules. 7 days rolling averages and standard deviations are computed to capture short-term fluctuations and longer-term trends in energy usage. This step also involved converting operational data of appliances into binary states—active (on) and inactive (off)—based on energy consumption thresholds, which facilitated subsequent analyses of operational flexibility. Based on the data collected, specific energy and time features are chosen, such as day of the week, time of day, current and past energy usage, outdoor temperature, and energy variations. Additional features, such as clustering the source data and segmenting consumption patterns, are then engineered.

B. Shiftable Appliances Flexibility

This step involves the flexibility quantification and forecasting of shiftable appliances. Shiftable appliances, by their very nature, offer an opportunity to make adjustments in their operating periods. Flexibility of shiftable appliances refers to the adjustment of the appliance operating time in response to a signal from the aggregator while remaining within the consumer comfort level.

In the proposed methodology, dynamic comfort zones are determined to adjust energy usage strategies to both temporal patterns and consumer preferences in real-time. It involves segmenting daily operational data of shiftable appliances into three distinct clusters that represent varying levels of user comfort and energy demand. These temporal comfort zones are dynamic and are updated weekly to reflect recent changes in user behavior due to economic, environmental, and appliance interaction patterns. A high comfort zone represents frequent appliance activity, indicating less opportunity for flexible operations; a moderate comfort zone represents medium appliance activity, while a low comfort zone indicates that the appliance is highly unlikely to be switched on at that time range; thus, no flexible opportunities. Let D_i represent the binary operational status of an appliance at a time interval i , where $D_i = 1$ if the appliance is on, and $D_i = 0$ if the appliance is off. For each week w , the aggregated operational states for each discrete time interval t is formulated as:

$$F_w(t) = \sum_{i=1}^{N_w} D_i \text{ where } t \in [1, T] \quad (1)$$

Where N_w is the total number of days in a week w , and T is the total number of time intervals in a day. K-means clustering is applied to the aggregated weekly data $F_w(t)$ to identify three distinct clusters and dynamically assign each time interval to a comfort level cluster based on appliance operational periods and duration:

$$C_w(t) = KMeans(F_w(t), n_{clusters} = 3) \quad (2)$$

Where, $C_w(t)$ is the cluster assignment for the time interval t in a week w . This clustering strategy captures the inherent variability in appliance usage and adapts to weekly shifts in operational patterns, thus providing a robust framework for managing and predicting demand-side flexibility.

The flexibility quantification of shiftable appliances involves measuring their actual usage within each dynamic comfort cluster and calculating the potential for operational shifts while considering that the power consumption of each appliance remains constant during its operational periods. For each day of the week w and within each comfort cluster c , the total operational duration $O_d(c)$ for a given appliance is computed as:

$$O_d(c) = \sum_{t \in C_w(c)} D_i \Delta t \quad (3)$$

where D_i denotes the binary states of the appliances and Δt is the duration of each time interval. By utilizing the maximum allowable operating time T_c within each cluster, the flexibility of shiftable appliances for a given day d is represented as:

$$F_{s,d}(c) = P(T_c - O_d(c)) \quad (4)$$

where $F_{s,d}(c)$ indicates the difference between the maximum allowable operating time T_c and the actual operational duration $O_d(c)$ of the appliance in that cluster, and P is the rated power of the appliance. This difference represents the potential time period during which the operation of the appliance can be adjusted—either advanced or deferred—thereby contributing to more efficient energy management.

To predict the temporal flexibility for the next day, the XG-Boost model is used for its ability to efficiently handle structured data, capturing non-linear relationships with minimal feature engineering and low computational demand. The input features for the model include past flexibility values from each comfort level, past appliance operating durations, time of the day, day of the week, and temperature forecasts. Past flexibility data is derived from operational metrics of appliances and aggregated into flexibility profiles based on historical usage patterns under different comfort zones. XG-Boost employs a gradient boosting framework that optimizes a loss function through boosting, effectively learning from the previous predictions' residuals. The model is formulated as:

$$\hat{F}_{s,d+1}(c) = XGBoost \left(\begin{matrix} F_1(c), F_2(c), \dots, F_n(c) \\ H_d, Temp_{d+1} \end{matrix} \right) \quad (5)$$

where $\hat{F}_{d+1}(c)$ is the predicted temporal flexibility for cluster c on day $d + 1$ and H_d is the appliance's operating duration. This methodological approach enables a detailed analysis of when and how much each appliance can be flexibly operated, providing a quantitative basis for implementing demand-response strategies.

C. Thermostatically Controlled Appliances Flexibility

TCA's represent a significant component of residential heating and cooling systems, offering unique opportunities for demand-side flexibility and energy management strategies. The flexibility of TCA's refers to the feasible adjustments in their operations by ramping up or down the power consumption depending on the consumer's comfort. In the proposed methodology, the flexibility of TCA's is quantified by analyzing their operational patterns and adapting to dynamic consumer comfort levels while considering external environment conditions. K-means clustering is employed on the hourly aggregated binary data to categorize the operational patterns of heat pumps into distinct clusters of higher and lower comfort zones. To quantify the flexibility of TCA, weights σ are assigned to each cluster based on operational intensity, which is inversely proportional to their flexibility potential, with higher weights indicating lower operational flexibility due to high usage intensity. These weights are given as:

$$\text{High Comfort Zone: } \sigma_{High} = 1 - \frac{\sum_{i=1}^{n_{High}} TCA_{ON,i}}{n_{High}} \quad (6)$$

$$\text{Low Comfort Zone: } \sigma_{Low} = \frac{\sum_{i=1}^{n_{Low}} TCA_{ON,i}}{n_{Low}} \quad (7)$$

Where n_{High} and n_{Low} are the total number of hours in high and low comfort zones. The flexibility of TCA's at time t is given as:

$$F_T(t) = \bar{E}(t)(1 - \sigma) \left(1 + \frac{E_{std}(t)}{\bar{E}(t)} \right) Temp_f(t) \quad (8)$$

Where $\bar{E}$ and E_{std} are the mean and standard deviation of TCA energy consumption, calculated for each hour by using a 3-day rolling window approach by creating sequential data to provide a measure of variability. $Temp_f$ is the temperature factor that adjusts the flexibility based on the predicted next-day temperature and is normalized between 0.8 and 1.2. It is calculated as:

$$Temp_f(t) = 1 - 0.2 \left(\frac{Temp(t) - Temp_{min}}{Temp_{max} - Temp_{min}} \right) + \beta \quad (9)$$

Where $Temp_{max}$ and $Temp_{min}$ are the historical minimum temperature for similar times of the year. β is the scaling factor that provides a buffer to prevent extreme adjustments in the flexibility quantification. To predict the flexibility for the next day, XG-Boost model is trained on the input features derived from historical data. The model is represented as:

$$\hat{F}_{T,d+1}(t) = XGBoost \left(\begin{matrix} (F_1(t), F_2(t), \dots, F_n(t), \sigma, \\ \bar{E}(t), E_{std}(t), Temp_f(t)) \end{matrix} \right) \quad (10)$$

where $\hat{F}_{T+1}(t)$ is the predicted flexibility of TCA for hour t on day $d + 1$. This methodology provides a robust predictive tool for managing the flexibility of thermostatically controlled appliances, by considering consumer demands and weather conditions.

IV. RESULTS AND DISCUSSION

The proposed flexibility quantification and forecasting models are assessed using a real-world dataset, AMPDs, and developed in Python on PyCharm IDE. The AMPDs dataset provides two years of energy consumption data for individual home appliances, recorded at one-minute intervals in conjunction with weather data. For shiftable appliance flexibility analysis, dishwasher data with a power rating of 750W is used and transformed into 30-minute intervals, while for TCA flexibility analysis, heat pump data is used and transformed into 1-hour intervals to save computational time. After performing data preprocessing, a binary representation of dishwasher and heat pump usage is created by choosing a suitable threshold value. Fig.1 shows the dishwasher and heat pump energy consumption data after preprocessing.

The flexibility quantification process of the dishwasher starts with the mapping of dynamic consumer comfort. For each week, cumulative data is computed from the beginning of the dataset up to the current week, which means that as new data points are added week by week, the data on which the clustering is based grows. The data is grouped by time, and the total activations of the dishwasher are used as features for clustering. K-means clustering identifies three distinct comfort zones to highlight variation in consumer behavior towards appliance usage. Fig. 2 shows the dynamic nature of consumer comfort towards dishwasher usage. By considering the consumer comfort and appliance operating duration, the flexibility of the dishwasher is quantified using (4).

By utilizing past flexibility data, appliance operating durations, and weather conditions, XG-Boost is used to predict the flexibility of dishwasher for the next day. The proposed flexibility forecasting model is compared with another machine learning model - decision tree and performance is assessed using mean absolute error (MAE) and root mean square error (RMSE).

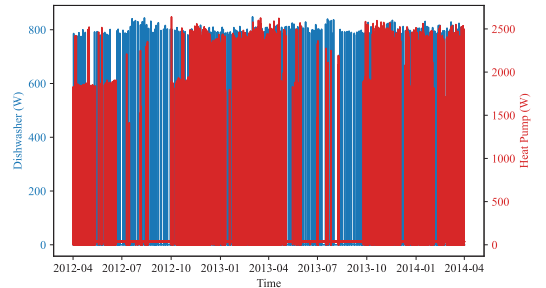


Fig.1. Dishwasher and heat pump power consumption over time.

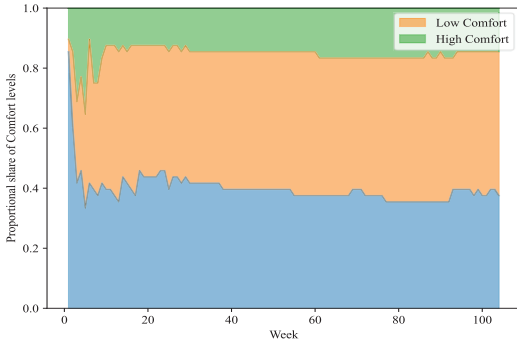


Fig. 2. Dynamic variations of dishwasher clusters across weeks.

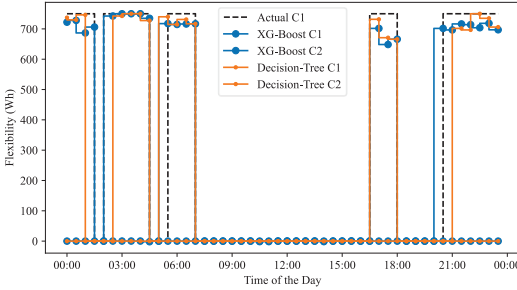


Fig. 3. Comparison of the day-ahead flexibility of the proposed model and Decision Tree algorithm.

Fig. 3 highlights the comparison of the actual flexibility of dishwasher with the forecasted flexibility using XG-Boost and Decision Tree algorithms in high and low comfort zones. Fig.4 shows the actual appliance operation and forecasted available flexibility regions under high and low comfort zones where the appliance can be shifted.

The total available flexibility capacity predicted by the XG-Boost model is 8.19 kWh within both comfort zones. This flexibility does not imply that the dishwasher itself will consume more than its fixed usage of 2.25 kWh (750W over 3 hours). Instead, it indicates the potential energy savings or shifts that can be achieved by strategically adjusting the operating times of the dishwasher within these comfort zones.

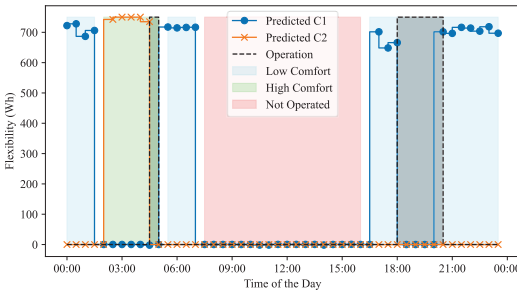


Fig. 4. Actual appliance operation and forecasted flexibility under different comfort zones

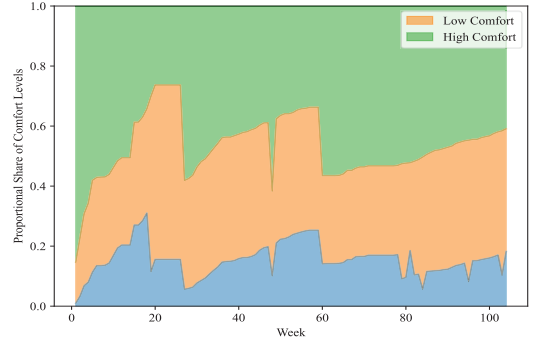


Fig. 5. Dynamic variations of heat pump clusters across weeks.

To analyze the flexibility of heat pump, Fig. 5 illustrates the dynamic changes in consumer comfort levels toward heat pump usage across each week, segmented by low and high comfort clusters. Fig. 6 highlights the comparison of the actual flexibility of the heat pump with the forecasted flexibility using XG-Boost and Decision Tree algorithms. Fig.7 shows the actual heat pump operation and forecasted available flexibility regions under high and low comfort zones where the appliance can be shifted.

The comparison of flexibility forecasting by different algorithms is shown in Table I. From the results, it is observed that the XG-Boost algorithm shows better forecasting precision than the Decision Tree algorithm as it shows lower MAE and RMSE, as shown in Table II.

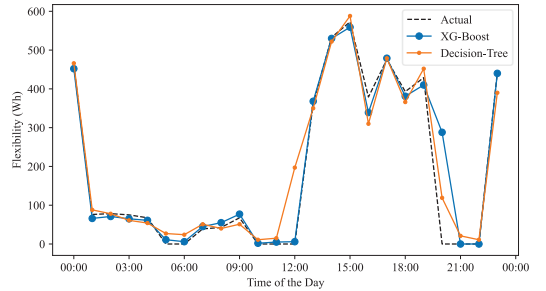


Fig. 6. Comparison of the day-ahead flexibility of the proposed model and Decision Tree algorithm.

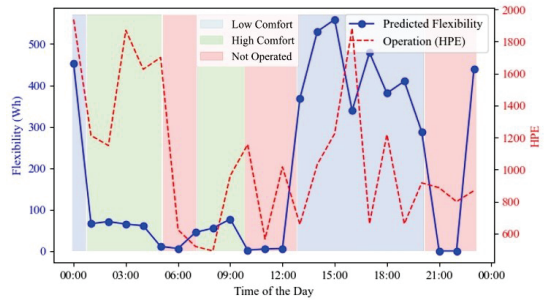


Fig. 7. Actual heat pump operation and forecasted flexibility under different comfort zones.

TABLE I.
COMPARISON OF FLEXIBILITY FORECASTING OF DIFFERENT ALGORITHMS

Appliance	Comfort Level	Actual Flexibility (kWh)	Predicted Flexibility (kWh)	
			XG-Boost	Decision Tree
Dishwasher	Low	7.87	6.33	5.38
	High	2.25	1.86	1.49
Heat pump	Low	4.04	4.24	4.21
	High	0.44	0.47	0.53

TABLE II.
COMPARATIVE PERFORMANCE TO DIFFERENT ALGORITHMS

Appliance	Forecasting Algorithm	MAE	RMSE
Dishwasher	XG-Boost	0.06	0.20
	Decision Tree	0.18	0.41
Heat pump	XG-Boost	0.04	0.11
	Decision Tree	0.05	0.09

Demand-side flexibility forecasting enables flexibility aggregators to effectively manage and allocate energy resources without compromising user comfort. This is crucial during peak demand or during ancillary services provision, facilitating more responsive and cost-effective energy provision.

V. CONCLUSION

The study developed a comprehensive methodology to forecast the demand-side flexibility of household appliances by quantifying flexibility with dynamic consumer behavior and forecasting its availability using machine learning techniques, specifically XG-Boost and K-means clustering. These models integrated historical data analysis and predictive modeling under varying operational and environmental conditions. The results demonstrated effective flexibility quantification and forecasting for both shiftable appliances like dishwashers and thermostatically controlled appliances (TCAs) like heat pumps. The models' performance was validated against other machine learning approaches, such as Decision Trees, with XG-Boost showing superior forecasting precision, with an MAE of just 0.06 for dishwashers and 0.04 for heat pumps. This research enables energy aggregators to optimize their portfolio management, facilitating the provision of flexibility services that respond dynamically to consumer behavior and market demands. In the future, research will be focused on including EV and energy storage as well as flexibility forecasting modeling.

ACKNOWLEDGMENT

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Appendix 6

Publication VI

A. Shahid, A. Rosin, R. Ahmadiyahangar, and T. Korötko, “Load Rebound Effect in Demand-side Flexibility: Analyzing the Impacts on Grid Stability,” IEEE International Conference on Power Systems and Electrical Technology (PSET), pp. 843–847, Aug. 2025, doi: 10.1109/pset66242.2025.11296529.

Load Rebound Effect in Demand-side Flexibility: Analyzing the Impacts on Grid Stability

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Abstract—With the increasing share of renewable energy in modern power systems, new energy management policies are being developed to support independent flexibility aggregation and facilitate the creation of balancing markets as efficient energy trading platforms. Load-rebound peaks that follow demand-side flexibility (DSF) events are an under-explored threat to isolated renewable microgrids, creating potential stability issues. This paper uses a real-time digital simulator (RTDS) to analyze the rebound-induced frequency excursions on an islanded grid comprising PV, wind, and diesel generation. By simulating various scenarios of load shifting and their corresponding rebound effects, the study examines its implications for grid stability and introduces a behaviour-aware control layer to suppress them. The paper proposes an adaptive comfort analysis strategy for flexibility aggregation, utilizing dynamic consumer behavior analysis to mitigate the rebound effect. The findings highlight the frequency regulation challenges posed by the load rebound effect, presenting results such as a peak frequency deviation of 0.46 Hz during over-rebound scenarios. The study enables aggregators and DSF market designers to set evidence-based rebound limits and reserve margins for stable, cost-effective microgrids.

Keywords—rebound effect, demand-side flexibility, real-time digital simulator, frequency regulation

I. INTRODUCTION

The transition towards renewable energy sources (RES) is transforming modern power systems, driven by the urgent need to reduce greenhouse gas emissions and achieve sustainable energy goals [1]. The increasing penetration of RES, such as photovoltaic (PV) and wind energy, introduces significant variability and uncertainty into the grid while reducing the system, thereby necessitating an increasing need for demand-side flexibility (DSF) to maintain grid stability [2]. In response to these challenges, European countries are advancing new legal frameworks and energy policies to support independent flexibility aggregation. These policies aim to facilitate the participation of various actors, including independent aggregators, in various grid ancillary services and energy markets. These markets serve as platforms for energy trading to manage and settle energy transactions, ensuring that the aggregated demand-side resources can be utilized efficiently to maintain grid stability [3].

Flexibility in energy systems is provided through various mechanisms, including demand response, energy storage, and flexible generation. These assets include HVAC systems, electric vehicles, battery energy storage systems (BESS), and other demand-response capable devices [4]. These assets facilitate the adjustment of electricity consumption or

production in response to grid demands. Aggregators combine flexibility assets by making contracts with residential consumers or industrial facilities. They trade these aggregated flexibilities in energy markets in return for adjusting energy consumption by shifting energy use to off-peak times, reducing consumption during peak demand periods, or temporarily increasing usage to absorb excess generation [5].

A notable issue within the evolving landscape of modern power systems is the rebound effect that occurs when the temporarily reduced or shifted load returns to the grid after the flexibility service period ends [6]. Fig. 1 illustrates the load rebound effect following a load-shifting event. This effect leads to a rebound peak in demand that undermines the benefits of the initial flexibility event, causing grid instability, increased generation costs, and frequency control issues. For instance, HVAC systems, when temporarily turned off for flexibility, may create a surge in demand upon resuming operations to restore desired temperatures. The rebound effect is not uniform; it varies in response time, magnitude, and duration. This paper highlights the importance of the rebound effect in developing and assessing flexibility aggregation strategies. A case study is presented using a real-time digital simulator (RTDS), focusing on frequency control within an islanded grid environment. The RTDS setup allows for high-fidelity, real-time simulations, making it an ideal tool for modeling complex power systems and analyzing their dynamic behavior under different operating conditions. An adaptive comfort management strategy is proposed to enable aggregators to mitigate the impacts of the rebound effect by tapping into the comfort zone, where more temporal range shifts in appliance usage are available.

This work contributes: (1) the first RTDS-based analysis of rebound frequency excursions in islanded grids; (2) a behaviour-aware comfort-clustering algorithm to pre-empt rebounds.

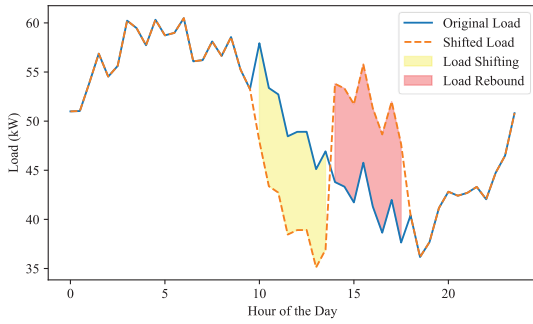


Fig. 1. Rebound effect after load shifting event.

II. CAUSES AND MITIGATION STRATEGIES FOR REBOUND EFFECT

The load-rebound effect emerges from multiple sources, each contributing to the increased demand following a flexibility event. HVAC systems, when turned off or when their temperature setpoints are reduced during flexibility periods, require more power to restore desired temperatures once the flexibility period ends, resulting in a significant surge in electricity demand [7]. Deferred charging of electric vehicles causes congestion problems, creating large demand spikes when charging resumes [8]. Similarly, improper management of BESS charging and discharging cycles leads to demand peaks, especially if charging is concentrated during certain periods [9]. Household appliances and industrial processes also contribute to the rebound effect [10]. Regarding the mitigation of the load rebound effect, various strategies can be employed, including staggered load resumption, dynamic pricing models, enhanced predictive analytics, increased energy storage, and real-time monitoring and control systems. These approaches can significantly reduce the negative impacts, thereby ensuring grid stability and efficiency [12], [13]. Additionally, proper regulatory and policy interventions are crucial in encouraging best practices for managing flexibility assets [14]. Based on typical industrial knowledge, Table I highlights the impact of various flexibility assets on load rebound with different mitigation approaches.

In [15] a reinforcement learning-based decentralized community energy management is proposed to mitigate peak rebound by optimizing BESS scheduling and total community cost. A customer incentive pricing model is presented in [16], in which appliance scheduling is optimized by a centralized genetic algorithm-based approach. A quantitative method of HVAC power flexibility in office buildings is proposed by [17]. Buildings with high flexibility participate more in power grid response but have low load rebound suppression ability. In [18], the rebound effect is controlled using a dynamic baseline in a look-ahead scheduling scheme within a column generation-based distributed scheduling model. In [19], the rebound effect is controlled by incorporating a peak-to-average ratio (PAR) incentive into the time-of-use (TOU) pricing scheme, which discourages deferrable load accumulation during low price periods by offering discounts to customers. Current research focuses on providing grid ancillary services through DSF initiatives, with relatively few studies examining the rebound effect. This rebound effect requires further research and exploration due to its significant implications for grid stability and efficiency.

TABLE I. COMPARISON OF FLEXIBILITY ASSETS AND THEIR IMPACT ON LOAD-REBOUND

Flexibility Asset	Rebound Impact	Typical Rebound Peak (kW)	Mitigation Strategy
HVAC Systems	High	2.5	Staggered Resumption
Electric Vehicles	Medium	3.0	Dynamic Pricing, Predictive Models
BESS	Medium	1.5	Increased Storage Capacity
Industrial Processes	High	5.0	Real-Time Monitoring, Scheduling
Household Appliances	Low	0.8	Optimized Charging Cycles

III. ANALYSIS OF REBOUND EFFECT USING RTDS

To examine the rebound effect on energy flexibility in modern power systems, various scenarios are developed using an RTDS-based islanded grid. This grid comprises PV, wind turbines, a diesel generator, and multiple loads to simulate different conditions under which load shifting and subsequent rebound effects occur. The study aims to evaluate the impact of these scenarios on grid frequency stability.

A. Scenario 1: Partial Load Rebound with Intermittent Renewable Generation

In this scenario, a day is simulated with highly intermittent renewable generation, characterized by cloudy weather affecting solar output and variable wind speeds for wind turbines. Following strategic load shifting for flexibility services, the system's response to a partial rebound of 80% of the shifted load is analyzed. Fig. 2 shows the result of this simulation on RTDS. Initially, the frequency stabilizes back to normal from 59.76 Hz due to the aggregators' flexibility services. However, a transient frequency reduction to 59.81 Hz is observed when the load rebounds. This secondary frequency variation highlights the need for aggregators to enhance their disaggregation strategies to manage the rebound effect.

B. Scenario 2: Full Load Rebound to Initial Baseline

In the second scenario, the load-shifting event is followed by the load returning to its initial pre-shifted baseline level. As demonstrated in Fig. 3-4, this full rebound results in a significant frequency change, dropping to 57.74 Hz due to the rebound effect. This scenario illustrates the substantial impact of a complete load rebound on grid stability and underscores the importance of managing load recovery to prevent large frequency deviations.

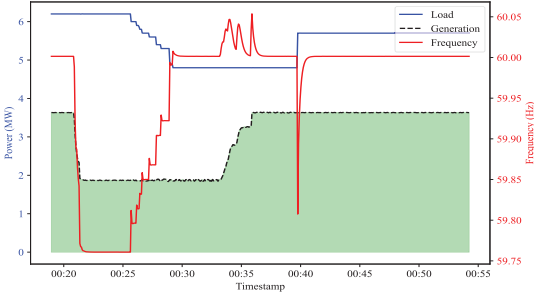


Fig. 2. Frequency change due to partial load rebound

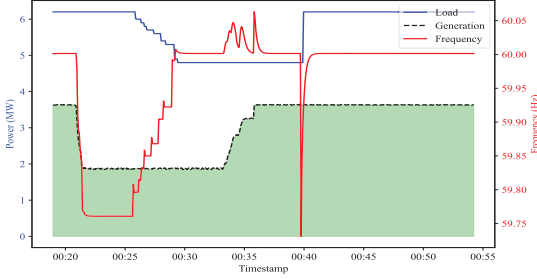


Fig. 3. Frequency change due to full load rebound.

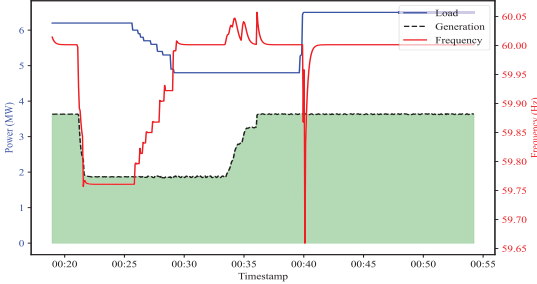


Fig. 4. Frequency change due to over-rebound

In modern power systems, maintaining a steady frequency is essential. Understanding the timing and magnitude of frequency deviations from a set point is essential for evaluating system stability. To analyze system stability, an absolute deviation plot is used to illustrate the frequency variations caused by the rebound effect under different scenarios, as depicted in Fig. 5. Table II highlights the impact of the rebound effect across these three scenarios. These simulation scenarios provide valuable insights into the challenges posed by load-rebound effects on frequency regulation within islanded grids.

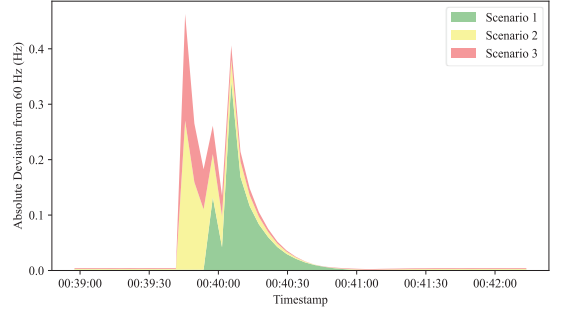


Fig. 5. Cumulative impact of frequency deviation across various scenarios.

TABLE II. IMPACT OF REBOUND EFFECT ON GRID FREQUENCY

Scenarios	Impact Duration (sec)	Peak Frequency Deviation (Hz)
Partial Load Rebound	21	0.32
Full Load Rebound	25	0.39
Over Rebound	26	0.46

IV. ADAPTIVE COMFORT ANALYSIS FOR FLEXIBILITY AGGREGATION

The rebound effect presents significant challenges for grid stability and effective energy management. To mitigate this effect, an adaptive consumer comfort analysis using k-means clustering is proposed for aggregators to optimize flexibility by dynamically classifying appliance usage patterns into two comfort zones: higher comfort - where consumers have higher comfort preferences, implying less flexibility and lower comfort - where consumers have lower comfort preferences, implying more flexibility.

The process starts by collecting energy consumption data for various household appliances, such as HVAC systems, lighting, and washing machines, and extracting features such as temperature setpoints, appliance duration, occupancy, and others. Let $X_i(t)$ be the feature vector for household i at time t . These features include average daily usage, peak usage times, duration of appliance use, and frequency of use.

$$X_i(t) = [x_{i1}(t), x_{i2}(t), \dots, x_{ij}(t)] \quad (1)$$

where, $x_{ij}(t)$ is the j -th feature at time t .

K-means clustering is applied to classify the usage patterns into two clusters: higher comfort zone and lower comfort zone. By initializing $k = 2$, each data point $X_i(t)$ is assigned to the nearest centroid μ_j . These centroids are then updated based on the set-points C_j until converged.

$$\mu_j = \frac{1}{|C_j|} \sum_{X_i(t) \in C_j} X_i(t) \quad (2)$$

To dynamically update the clusters, at the end of each week, the feature vector of the new week's data is incorporated into the previous dataset, and the k-means algorithm is re-run to update the clusters.

$$X_i^{new}(t) = [x_{i1}(t - \tau), x_{i1}(t - \tau + 1), \dots, x_{ij}(t)] \quad (3)$$

where τ is the number of previous weeks considered. The clusters C_j are recalculated using the updated dataset. Updated centroids are given as:

$$\mu_j^{new} = \frac{1}{|C_j^{new}|} \sum_{X_i^{new}(t) \in C_j^{new}} X_i^{new}(t) \quad (4)$$

For each household i , the comfort zones are defined based on these clusters.

$$Comfort = \begin{cases} Z_{i,higher} = X_i(t) \in C_1 \\ Z_{i,lower} = X_i(t) \in C_2 \end{cases} \quad (5)$$

During a demand-side flexibility event, if a rebound effect is anticipated, the aggregator utilizes these comfort zones by prioritizing shifting appliance usage to the lower comfort zone:

$$Shift_i(t) = \begin{cases} Z_{i,lower} & \text{if rebound} \\ Z_{i,higher} & \text{otherwise} \end{cases} \quad (6)$$

This dynamic adjustment will ensure that flexibility is maximized while minimizing discomfort to consumers. The clustering algorithm is retrained offline weekly using newly acquired usage data. While the algorithm updates its centroids periodically, real-time flexibility operations rely on the most recent offline-trained cluster labels

To analyze adaptive comfort, data from five houses is used to illustrate how aggregated flexibility can be represented at an aggregator level. Each house has its own profile for higher and lower comfort zones over a 12-hour period.

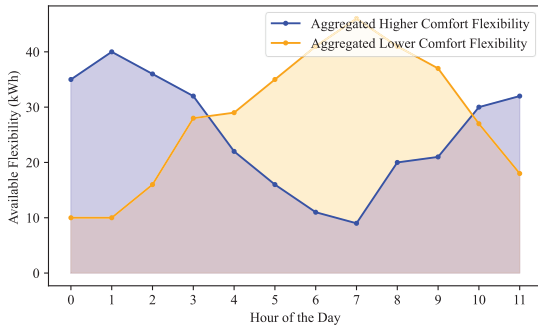


Fig. 6. Aggregated Flexibility Availability with adaptive comfort zones.

Fig. 6 represents the aggregated flexibility at an aggregator level, showcasing higher and lower comfort zones throughout a 12-hour period.

This approach provides a comprehensive view of the temporal dynamics of the flexibility landscape available to an aggregator. It helps in making informed decisions to effectively balance grid stability and consumer comfort while mitigating load rebound effects.

V. CONCLUSION

This study highlights the critical challenges posed by the rebound effect on grid stability within modern power systems that heavily rely on renewable energy sources. The real-time evidence using RTDS is provided about rebound that can drive islanded-grid frequency outside statutory limits within 30 s. The results revealed significant deviations, particularly in over-rebound scenarios, highlighting the need for precise management strategies. To address these issues, the paper

proposed an adaptive comfort analysis strategy using dynamic consumer behavior analysis and k-means clustering. This strategy allows aggregators to optimize flexibility aggregation by categorizing appliance usage into higher and lower comfort zones, thereby mitigating the rebound effect. These findings emphasize the importance of effective flexibility asset management for aggregators and the utilization of adaptive strategies to enhance grid stability and ensure a cost-effective and resilient energy system. In the future, research will focus on developing more advanced flexibility aggregation strategies and leveraging reinforcement learning for optimal control of flexibility assets, thereby improving aggregation and control energy buffer requirements.

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Appendix 7

Publication VII

A. Shahid, R. Ahmadiyahangar, A. Rosin, V. Maask, and J. Martins, "Exploratory Data Analysis for Demand-side Flexibility Quantification," IEEE International Conference on Compatibility, Power Electronics and Power Engineering, pp. 1–6, Jun. 2023, doi: 10.1109/cpe-powereng58103.2023.10227408.

Exploratory Data Analysis for Demand-side Flexibility Quantification

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Abstract—This research article explores various methods for quantifying demand-side flexibility and focuses on one particular technique based on power consumption. The study performs exploratory data analysis on the AMPDs dataset in the time domain, encompassing trend and correlation analysis and attributes distribution analysis to highlight the importance of considering different factors influencing household power consumption. The analysis results are used to aid in the feature selection and extraction process of machine learning model development for determining demand-side flexibility through power consumption. This article provides valuable insights for researchers and practitioners in the energy industry looking to better understand demand-side flexibility and estimate its quantification.

Keywords— *energy consumption, flexibility, exploratory data analysis, weather, temperature, visualization*

I. INTRODUCTION

Demand-side Flexibility (DSF) refers to the ability of electricity consumers to adjust their energy consumption patterns in response to changes in electricity prices, grid conditions, or incentives. DSF plays an increasingly important role in the transition towards a more sustainable and decarbonized energy system. By allowing consumers to adjust their energy consumption in response to changes in the grid, DSF can help to create a more efficient and balanced energy system [1].

DSF can be achieved through various mechanisms, including demand response programs, smart grid technologies, and energy-efficient appliances. Demand response programs allow consumers to adjust their energy consumption in response to changes in electricity prices, for example, by shifting their energy usage to times when electricity is cheaper. Smart grid technologies, such as smart meters, provide consumers with real-time information on their energy consumption, allowing for more accurate and efficient energy management. Energy-efficient appliances, such as

smart thermostats and refrigerators, can also help to reduce energy consumption by optimizing energy usage based on consumer behaviour and grid conditions [2].

One of the key benefits of DSF is that it helps to reduce the strain on the electricity grid, especially during periods of high demand. By allowing consumers to shift their energy consumption to times when electricity is cheaper, DSF can help to reduce the need for expensive peak power generation, which can be generated from fossil fuels and reduce the risk of power outages and blackouts. It can help to reduce greenhouse gas emissions and support the transition towards a more sustainable energy system [3].

DSF also helps to reduce energy costs for consumers. By shifting energy consumption to times when electricity is cheaper, consumers can reduce their overall energy bills. Additionally, energy-efficient appliances can help to reduce energy consumption and lower energy bills over the long term.

In order to fully realize the benefits of DSF, it is necessary to accurately quantify its potential. It involves analyzing consumer behaviour and energy consumption patterns and considering the impact of external factors such as regulations, incentives, weather conditions, and consumer preferences. The results of this analysis can then be used to develop smart machine learning (ML) based strategies for increasing demand-side flexibility and optimizing energy consumption.

In the literature, many quantification methods are used for energy flexibility. However, no one best quantification method fits every use case; thus, the quantification method depends on the type of flexibility being quantified. To achieve reliable quantification of DSF, it is necessary to carry out a thorough exploratory data analysis (EDA). This emphasizes the graphical representation by collecting and analyzing data on consumer behaviour and energy consumption [4].

EDA is a critical component of data science and statistical analysis. It is a systematic approach to understanding and

analyzing data sets to gain insights, identify patterns and trends, and formulate hypotheses. EDA is the first step in a larger data analysis process, and it plays a crucial role in gaining a deeper understanding of the data being analyzed.

The goal of EDA is not to reach a final conclusion but rather to gain a preliminary understanding of the data and identify any potential areas for further investigation. EDA involves several techniques for analyzing and visualizing data, including descriptive statistics, frequency distributions, and graphical representations such as histograms, scatterplots, and box plots. These techniques are used to summarize and describe the data, identify outliers and anomalies, and examine the relationships between variables. In addition, EDA can also involve statistical modelling and hypothesis testing, where the analyst uses statistical methods to test hypotheses about the data [5].

EDA is a critical component of data analysis, and it is used in a wide range of applications, including scientific research, business and economics, and engineering. EDA provides a foundation for more advanced statistical methods, such as regression analysis, machine learning, and predictive modelling. By gaining a deeper understanding of the data, EDA helps to inform these advanced techniques, leading to more accurate and effective results.

This paper presents a comprehensive investigation into the various techniques employed for quantifying flexibility. The authors introduce a novel, generalized model for the measurement of power-dependent flexibility and provide an extensive exploratory data analysis of the Almanac of Minutely Power dataset (AMPDs) to validate the efficacy of this approach.

II. LITERATURE REVIEW

The development of smart grid technologies and the integration of renewable energy sources into the grid have increased the need for demand-side flexibility. Several studies have investigated methods for quantifying demand-side flexibility, including traditional engineering approaches and data-driven methods [6]. Engineering approaches typically rely on energy simulations and models, which can provide a static view of the system and may not reflect the actual behaviour of energy consumers. On the other hand, data-driven methods use real-world energy consumption data to quantify flexibility and can provide a more dynamic and accurate view of the system.

[7] quantifies the energy flexibility by measuring the potential power increase or decrease that a system can sustain before reaching operational limits while taking into account various factors such as user comfort and system constraints. [8] uses a rule-based controller and model predictive controller to quantify the flexibility of a house. Similarly, regarding data-driven methods, [9] and [10] studied the energy flexibility of residential and commercial buildings using XG-Boost and cloud-based big data processing with LSTM, respectively. The studies analyzed the consumption patterns and power value distribution of flexible appliances and electric vehicles and evaluated the flexibility efficiency in a demand response model.

Exploratory data analysis (EDA) is a data-driven approach that has gained popularity in recent years for its ability to uncover patterns and relationships in energy consumption data. Several studies have applied EDA techniques to energy

consumption data, including time-series analysis, clustering, and dimensionality reduction. These techniques have been used to identify patterns of energy consumption, energy usage behaviour, and the impact of external factors (such as weather and energy prices) on energy consumption [11].

A. Various approaches for quantifying energy flexibility

Quantifying energy flexibility is crucial to assess a building's ability to adjust its energy consumption in response to changes in demand, supply, energy prices, carbon emissions, and other factors. Various parameters such as power, load shifting capacity [12], and energy cost is considered for flexibility measurement. Each of these parameters provides a different perspective on a building's energy consumption and its ability to adjust to changes in the energy landscape. The most common methods for measuring demand-side flexibility are given below:

- a) *Power-dependent flexibility*: This measures a building's ability to adjust its power consumption in response to changes in demand or supply. Power flexibility can be calculated by comparing the building's actual power consumption to its maximum or minimum power consumption under different scenarios.
- b) *Load shifting flexibility*: This measures a building's ability to shift its energy consumption from one time period to another. Load shifting can be calculated by comparing the building's energy consumption during peak periods to its energy consumption during off-peak periods.
- c) *Energy cost flexibility*: This measures a building's ability to adjust its energy consumption in response to changes in energy prices. Energy cost flexibility can be calculated by comparing the building's energy consumption when energy prices are high to its energy consumption when energy prices are low.
- d) *Carbon emission flexibility*: This measures a building's ability to adjust its energy consumption in response to changes in carbon emissions. Carbon emission flexibility can be calculated by comparing the building's energy consumption when emissions are high to its energy consumption when emissions are low.
- e) *Autonomous flexibility*: This measures a building's ability to adjust its energy consumption autonomously without human intervention. Autonomous flexibility can be calculated by comparing the energy consumption of the building under autonomous control to the energy consumption of the building under manual control.
- f) *Ancillary services flexibility*: This measures a building's ability to provide ancillary services such as frequency regulation, spinning reserve and voltage control. The flexibility of a building to provide such services can be calculated by comparing the real-time energy consumption of the building to its predicted energy consumption.

The aim of our study is to deliver a complete description of the data and to suggest a methodological EDA framework for application to power flexibility quantification emphasizing visualization methods. The results of the analysis will be used in identifying energy consumption patterns and behaviour,

supporting energy management decisions, evaluating the effectiveness of energy efficiency measures, and informing energy policy development, which will be a part of a framework for optimal planning of a largescale integration of renewable energy in which energy flexibility plays the dominant role.

III. METHODOLOGY

A. Data and methods

The AMPDs dataset used as a case study was provided by [13]. It is a publicly available dataset that contains detailed information on the energy consumption of a single residential building over a period of two years. The data was collected at a 1-minute resolution and included information on both active and reactive power. The dataset also includes information on weather data, such as temperature and humidity, as well as information on the occupancy of the building.

The AMPDs dataset is widely used in energy management research, particularly in the field of building energy management and demand response. It has been used in a variety of studies, including research on energy consumption prediction, load disaggregation, and demand response management. An overview of the AMPDs variables examined for EDA is shown in Table 1.

TABLE I. VARIABLES EXAMINED IN THE STUDY

Variable	Variable Type	Unit	Time Horizon
Timestamp	Date/Time	Date/Time	04/01/2012 - 03/30/2014
Household power consumption	Numeric	W	1 min (04/01/2012 - 03/30/2014)
Weather Condition	Categorical	N/A	04/01/2012 - 03/30/2014
Temperature	Numeric	°C	1 Hour (04/01/2012 - 03/30/2014)
Year	Date/Time	Year	2012 – 2014
HVAC power consumption	Numeric	W	1 min (04/01/2012 - 03/30/2014)

B. Power Flexibility

Power flexibility measures the building's ability to adjust its power consumption in response to changes in demand or supply. To calculate power flexibility, you would need to measure the building's maximum and minimum power consumption under different scenarios, such as different weather conditions, occupancy levels, or energy prices [14]. You can also calculate the power flexibility index by considering the ratio between the building's actual power consumption and the building's maximum or minimum power. A higher ratio indicates higher power flexibility. The measurement of power flexibility provides a quantitative understanding of the extent to which a system can adjust its power consumption or generation, which can then be used to inform decision-making and system design. Power flexibility can be according to equation (1).

$$\text{Power Flexibility} = P_{max}^i(t) - P_{min}^j(t) \quad (1)$$

where,

P_{max}^i = maximum value of building's power consumption under different scenarios, such as a hot summer day with high temperature

P_{min}^j = minimum value of building's power consumption under different scenarios, such as mild winter night with low temperature

Alternatively, the power flexibility index can be calculated using the following equation (2):

$$\text{Power Flexibility Index} = \frac{P_{Actual} - P_{min}^j}{P_{max}^i - P_{min}^j} \quad (2)$$

where,

P_{Actual} = actual value of the building's power consumption under a specific scenario, such as a day with a temperature of 20°C.

EDA is an important step in measuring power flexibility using the AMPDs dataset. EDA involves visualizing and summarizing the data to gain insights into the underlying patterns and relationships between the different variables. The insights gained from EDA can then be used to develop a machine learning model that can accurately predict the power flexibility of a residential building using the AMPDs dataset.

IV. EXPLORATORY DATA ANALYSIS FOR QUANTIFICATION

The quantification of flexibility is hindered by the lack of consistent patterns in individual residential loads. Unlike the electric load at the system level, the electricity consumption of a single household is highly influenced by the daily routines and lifestyle of its residents, as well as the types of major appliances they possess. This results in less predictable daily load profiles, which makes it challenging to quantify the flexibility of individual residential loads. EDA helps to identify the dominant patterns of electricity consumption, which can be used to understand the sources of variability in electricity consumption and is essential for accurately quantifying the flexibility of residential loads [15].

EDA is a critical step in the feature selection process to identify the most relevant and valuable features. EDA includes techniques like univariate analysis and correlation analysis to determine the distribution, presence of outliers, and the relationship between each feature and the target variable. Features that have a high correlation and little skew or outliers are considered significant and included in the analysis [16].

AMPDs dataset is a record of the energy consumption of a single house using 21 sub-meters at one-minute read intervals and includes hourly weather data such as temperature, humidity, and pressure, among others. The quality of the data is good, with some missing values and different time horizons. The dataset is refined using re-sampling and interpolation. Table 2 summarizes the visualizations utilized in the present study, serving as a useful reference for future studies that aim to gain a comprehensive understanding of the data. The table includes all the necessary visualizations to effectively analyze the data.

TABLE II. FIGURES OF THE PRESENT STUDY

Plot	Purpose	Variables	Figure
Box Plot	To identify the range and variability of the data, as well as outliers, the distribution of the data through quartiles	Weather, total power consumption	6
Categorical Plot	To understand the distribution of categorical data and identify relationships between categories	Temperature, HVAC power, month	4
Density Plot	To understand the distribution of the data and identify any skewness or outliers	HVAC power, weather	8
Histogram	To understand the distribution of the data and identify any skewness or outliers	Total power consumption	5
Line Chart	To understand the trends and patterns in the data over time	Total power consumption	1
Scatter Plot	To identify the relationship between two variables, including positive or negative correlations and outliers	Weather, total power consumption	2
Violin Plot	To identify the distribution and range of the data, as well as outliers	Weather, HVAC power consumption	7
2-D Kernel Density Estimation Plot	To understand the distribution and relationships between two variables by probability density function	Total power consumption, HVAC power, temperature	3

The graphical computation was performed using an Intel Core i7-4700MQ processor, equipped with 16GB of RAM and 4 CPU cores, operating on the Windows 10 platform with a clock speed of 3.40 GHz.

A. Trend and Correlation Analysis

The analysis of daily, weekly, and monthly electricity consumption trends is presented in Fig. 1. Daily consumption pattern informs about peak consumption, weekly consumption trends highlight the impact of work schedules and leisure activities on energy consumption, while monthly consumption trends reveal the seasonality of electricity consumption and the impact of environmental factors on energy consumption.

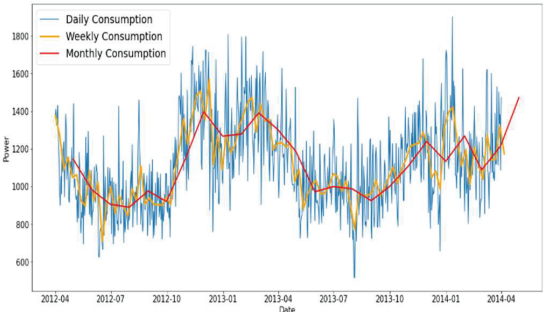


Fig. 1. Daily, weekly and monthly power consumption

A scatter plot, as shown in Fig. 2, with household energy consumption on the y-axis, the date on the x-axis and the hue representing the weather is a useful tool for analyzing the relationship between power usage and date while considering the impact of weather conditions. It allows for the examination of trends and patterns over time, comparison of the magnitude of power usage and identification of the effects of weather on power usage.

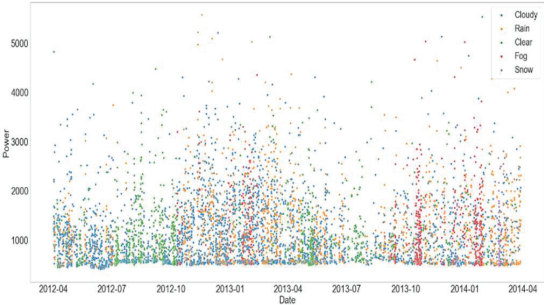


Fig. 2. Scatter Plot of Power Consumption under Different Weather Conditions

The two-dimensional Kernel Density Estimation (2D-KDE) plot in Fig. 3 shows the correlation between the household and HVAC energy consumption with temperature values. The 2D KDE plot is a non-parametric method that estimates the underlying probability density function of a random variable. The plot displays the density of data points, with areas of higher density representing areas where the data points are most concentrated.

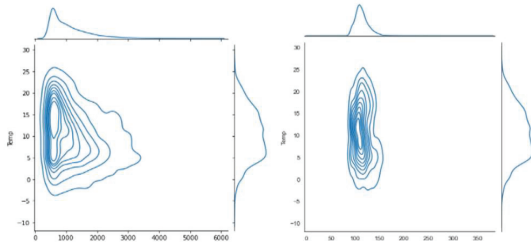


Fig. 3. 2D-KDE plot of temperature with household energy consumption (left) and HVAC energy consumption (right)

on the x-axis, and the curve on the right of the figure is a KDE plot for the data on the y-axis. The plot provides insight into the relationship between power consumption and temperature, indicating if there is a correlation between the two variables. The high density of data at 15°C for household energy consumption and at 10°C for HVAC suggests that there is an opportunity to reduce energy consumption by reducing energy consumption in those areas.

A categorical plot of temperature and HVAC power consumption by month, as shown in Fig. 4, highlights the long-term seasonal variation. While temperature peaked in July and August, there is no significant impact on HVAC energy consumption in the long term.

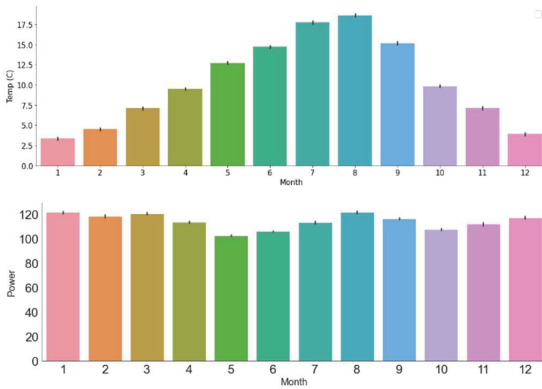


Fig.4. Monthly categorical plot for temperature (top) and HVAC energy consumption (bottom)

The trend and correlation analysis of the AMPDs dataset indicates a strong trend in the temperature variable and household energy consumption throughout the year, while HVAC energy consumption has no specific trend when discussing each of these variables individually. However, both household and HVAC energy consumption shows a strong correlation with temperature as the majority of their values lie in the temperature range of 10°C to 15°C. However, when it comes to power variations with weather conditions, there is no specific trend and correlation as from 07-2012 to 11-2012, weather is mostly clear with tracers of rain and clouds, but same in 2013, it is mostly fog.

B. Attributes Distribution Analysis

Fig 5. shows the distribution of electricity consumption over time. The inverse V-shape histogram indicates that the majority of the consumption occurs during the day, with consumption gradually increasing from morning to mid-afternoon and then decreasing towards the evening and night. This pattern is typically observed in households where residents are active during the day, engaging in activities that require electricity, such as cooking, washing, and using appliances and is extremely valuable in the quantification of flexibility as it provides insight into the variability of electricity consumption.

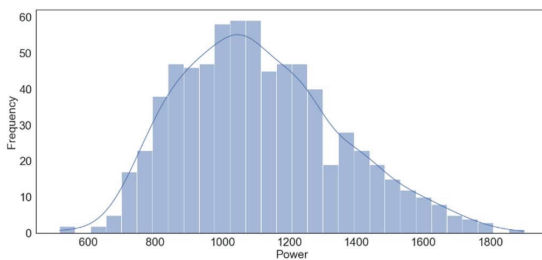


Fig.5. Histogram of household energy consumption

A box plot in Fig.6. of power consumption on the y-axis and weather on the x-axis shows the distribution of power consumption for different weather conditions. This type of plot provides an overview of the variability and central tendency of power consumption for different weather conditions, making it easier to identify any potential patterns

or relationships. The box plot displays a box (representing the interquartile range, IQR) between the first quartile (25th percentile) and the third quartile (75th percentile) of the power consumption data for each weather condition. The whiskers (lines extending from the box) represent the minimum and maximum power consumption, excluding outliers. Outliers are represented by individual dots and are typically displayed beyond the whiskers. Box plots are a useful tool for EDA as they provide a quick and easy way to visualize the distribution of a dataset, detect outliers, characterize the distribution, compare groups, and identify relationships between variables.

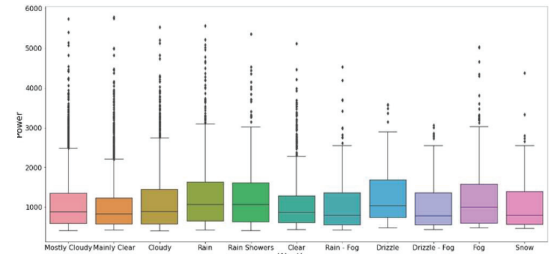


Fig.6. Box plot of household energy consumption under different weather conditions

A violin plot, shown in Fig.7, for HVAC power consumption gives information about the distribution of data values along with a representation of their range and frequency. It provides a visual representation of the shape of the distribution, including skewness, kurtosis, and outliers. Additionally, violin plots can provide information about the density and distribution of data, as well as a visualization of the interquartile range and median values. This information is useful for exploratory data analysis, as it provides insights into the underlying data patterns, distributions, and potential outliers that may need further investigation.

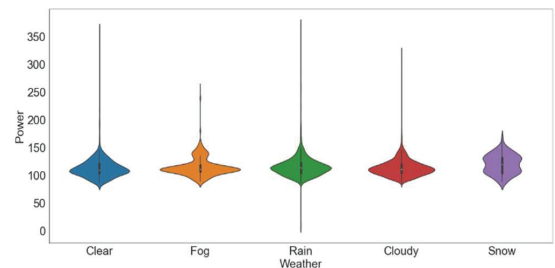


Fig.7. Violin plot of HVAC energy consumption under different weather conditions

In the context of HVAC power consumption and weather, the density plot can be utilized to analyze the flexibility of HVAC systems in different weather conditions. By plotting the HVAC power consumption against the hue of weather conditions, as shown in Fig.8, it is possible to identify patterns and trends in the data, such as how different weather conditions affect the power consumption of HVAC systems. This information can be used to optimize HVAC systems, reduce energy consumption, and increase efficiency.

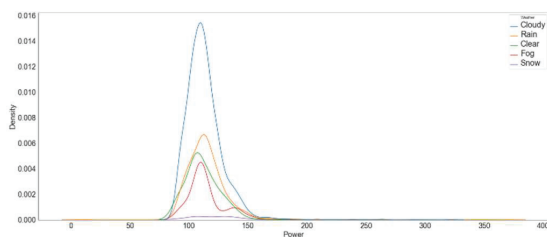


Fig.8. Density plot of HVAC consumption under different weather conditions

The above analysis shows that HVAC power data points are densely packed and narrow in cloudy weather conditions, which suggests that there is a strong relationship between power consumption and weather conditions.

V. CONCLUSION AND FUTURE WORK

To support sustainable development goals, demand-side flexibility can be the ultimate goal for building energy management. To reiterate, this work primarily focuses on two major aspects: energy flexibility measurement and exploratory data analysis using the AMPds dataset for flexibility quantification. The findings of this article are based on the eight different plots using total power consumption, HVAC power consumption, temperature, and weather data. These findings will be used for advanced data analytics modelling of flexibility quantification for efficient energy management in the future.

In this article, after preprocessing, graphical modelling of the AMPds dataset is used to determine the relationship between dependent and independent data features. Furthermore, KDE and violin plots show a strong correlation between the data features. Overall, this research has discussed the implementation of univariate analysis and data visualization through various exploratory data analyses to choose the most relevant data attributes for efficient building energy management. This involves the initial examination of data to summarize its main characteristics and to identify patterns, anomalies, and relationships within the data.

In the future, it is essential to explore the application of sensitivity analyses, case study methodologies and integration of real-time data with other datasets, such as weather data, energy market prices, or customer behavior data, to provide a more comprehensive understanding of DSF. This approach will also enhance the robustness and adaptability of the EDA techniques.

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Appendix 8

Publication VIII

A. Shahid, R. Ahmadiyahangar, A. Rosin, and T. Korötko, “Integrating BRP and Aggregator Roles for Imbalance Management and Frequency Regulation using Demand-side Flexibility,” IEEE Green Technologies Conference (GreenTech), pp. 1–6, Mar. 2026, doi: 10.1109/greentech68285.2026.11471579.

Integrating BRP and Aggregator Roles for Imbalance Management and Frequency Regulation using Demand-side Flexibility

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Abstract—Energy balancing costs significantly impact the operational efficiency of Balance Responsible Parties (BRPs), particularly in the context of increasing renewable energy integration and varying weather conditions that amplify forecasting uncertainties and frequency deviations in community-level energy systems. Imbalance settlement mechanisms often penalize deviations, exacerbating BRP operational costs. To address this challenge, this paper proposes a dual-role methodological framework for optimizing community-level flexibility resources when a balance responsible party (BRP) simultaneously acts as an aggregator providing frequency containment reserve for normal operation (FCR-N) services. The optimization is performed by minimizing the net operational costs, balancing day-ahead procurement costs, imbalance penalties, and maximizing FCR-N capacity and activation revenues simultaneously. Three distinct operational scenarios are analyzed: a baseline scenario without flexibility usage, flexibility dedicated solely to imbalance reduction, and flexibility fully committed to the FCR-N market. The analysis demonstrates that leveraging community-level flexibility for reserve services significantly reduced overall economic costs. Specifically, while committing the same flexibility solely to FCR-N resulted in substantial economic benefits, achieving an 4.75% cost reduction compared to the baseline. These savings primarily stemmed from substantial FCR-N capacity and activation payments, despite occasional increases in imbalance volumes due to reserve activations. The research highlights important trade-offs and operational considerations regarding frequency-dependent activations can influence BRP imbalance costs.

Keywords—energy imbalance, flexibility aggregation, balance response parties, frequency containment reserve, energy markets

I. INTRODUCTION

The growing integration of renewable energy sources, such as solar photovoltaic and wind power, into power grids has significantly increased variability and uncertainty, posing substantial challenges for system frequency stability [1]. To ensure stable grid operations, transmission system operators (TSOs) increasingly rely on ancillary services such as frequency containment reserve for normal operations (FCR-N), which require rapid and precise adjustments of power injection or consumption in response to frequency deviations [2]. While large conventional generators traditionally provide these services, distributed energy resources (DERs) such as battery energy storage systems (BESS), electric vehicles, heating, ventilation, and air conditioning (HVAC) systems, and shiftable appliances offer substantial untapped flexibility

potential that could effectively support frequency regulation [3].

European energy markets mandate balance responsible parties (BRPs) to maintain their declared energy schedules closely aligned with actual consumption or production, penalizing deviations through imbalance charges [4]. Consequently, BRPs often incur financial costs due to forecast inaccuracies [5]. An effective strategy to minimize such imbalance costs involves BRPs employing flexibility aggregation, thus adjusting consumption and production patterns proactively based on short-term forecasts and real-time market conditions. Recent research has explored the concept of integrating BRPs and aggregators; however, a systematic exploration involving simultaneous participation in both balancing and frequency regulation markets is limited.

Various market models have been proposed to structure interactions between aggregators, energy suppliers, and BRPs, including uncorrected, corrected, contractual, central settlement, and combined models [6]. Optimization models can help integrate ancillary services from demand-side management and distributed generation, considering interactions between transmission and distribution system operators [7]. [8] propose that a BRP can aggregate EV charging flexibility, turn it into “flexible orders,” and bid directly in the day-ahead market. Their simulations on the Danish power system show a 19 % reduction in energy procurement costs for the BRP compared to uncontrolled charging strategies. [9] introduces the concept of daily industrial flexibility (DIF), allowing BRPs to select cost-effective day-ahead industrial load profiles, with results showing 1.96% cost savings through an integrated MILP and electricity price forecasting approach. Balancing strategies for BRP portfolios with high wind generation and residential loads have also been explored, with simulations showing that shifting residential flexible demand can yield annual consumer profits of up to €20, emphasizing the role of automation in enabling flexibility integration [10]. [11] develop a data-driven quantification pipeline that aggregates household-level flexibility into market-ready reserve bids. [12] propose a two-stage probabilistic flexibility-management model for aggregated residential buildings that co-optimises ramping capacity and market revenues, lowering total BRP operating costs. [13] quantify the frequency-control value of aggregated residential battery systems in Belgium, showing grid-balancing benefits of at least 50% of the battery to frequency control yields returns on investment. [14] propose a machine learning-based framework for forecasting household-level demand-side flexibility, enabling aggregators

to improve portfolio optimization and avoid flexibility provision shortfalls.

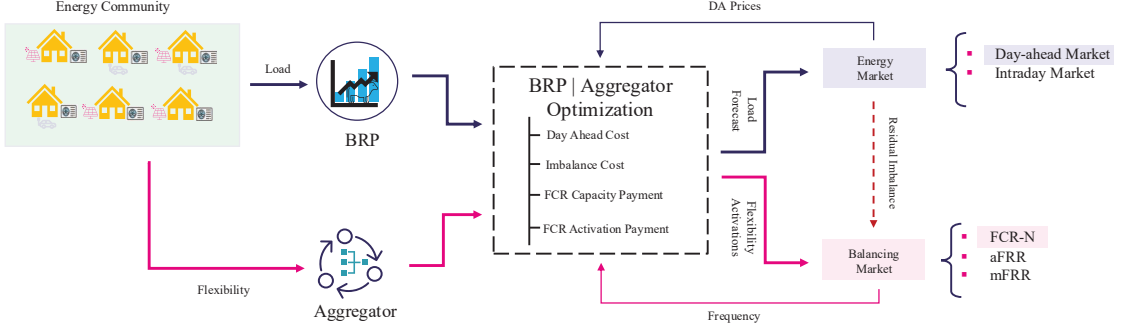


Fig. 1. MILP-based optimization framework for a BRP-aggregator to minimize imbalance costs.

Despite advances in flexibility aggregation and market participation, the literature lacks a framework that quantifies their combined economic impact under a hybrid BRP-aggregator model. The primary objective of this study is to demonstrate and quantify the economic and technical benefits of a hybrid BRP-aggregator model. Specifically, we investigate how leveraging aggregated household flexibility (BESS, EV charging, HVAC, and shiftable loads) can simultaneously reduce imbalance costs and provide profitable participation in the FCR-N market.

II. METHODOLOGY

Fig. 1 illustrates the methodology adopted to optimize BRP-aggregator operations by leveraging demand-side flexibility. It is designed to optimize the operational performance of a BRP serving as an aggregator, specifically targeting simultaneous cost minimization related to imbalance management and maximizing revenue from participation in the FCR-N market. The methodology adopts an integrated mixed-integer linear programming (MILP) framework capable of scheduling and dispatching aggregated residential flexibility resources, including BESS, HVAC units, and shiftable appliances.

Deviations between actual consumption and forecasted load result in imbalance volumes, settled at prices specified by imbalance settlement mechanism. In parallel, the BRP also acts as an aggregator participating in the Frequency FCR-N market by offering symmetrical flexibility derived from flexible resources. The optimization framework operates within the context of the Nordic electricity market structure, which involves multiple settlement intervals. Day-ahead (DA) scheduling decisions occur on an hourly basis, while imbalance settlements and FCR-N activations are accounted for at 15-minute imbalance settlement periods (ISPs). To accurately model these temporal characteristics, the proposed methodology discretizes the operational horizon into a series of 15-minute intervals $k = 1, \dots, N$, each representing an individual ISP, with a total of 96 intervals per day.

Within each ISP k , the actual metered load of the residential community is represented by L_k , and the forecasted load, based on the DA market commitment, is denoted by F_k . Consequently, the initial imbalance volume Δ_k at each interval is formulated as the difference between the actual consumption and the forecasted load:

$$\Delta_k = L_k - F_k \quad (1)$$

This imbalance is settled with the TSO at time-varying imbalance prices π_k^{imb} . The imbalance settlement cost C_k^{imb} is modelled as:

$$C_k^{imb} = \pi_k^{imb} \cdot \Delta_k \quad (2)$$

The BRP's first-level objective is to minimize this cost across all ISPs.

The methodology incorporates flexibility derived from three primary aggregated residential resources, represented as:

$$R_k = \{F_k^{BESS}, F_k^{HVAC}, F_k^{Shift}\} \quad (3)$$

The total available flexibility for each ISP is then aggregated into a symmetric reserve capacity envelope R_k^{commit} :

$$R_k^{commit} = \frac{\sum_{r \in R} F_k^r}{\Delta t}, \quad \Delta t = 0.25h \quad (4)$$

The FCR-N compensation includes two streams: A fixed price π_k^{cap} , or keeping flexibility available as reserve. The capacity payment C_k^{cap} is:

$$C_k^{cap} = \pi_k^{cap} \cdot R_k^{commit} \quad (5)$$

A variable payment based on the amount of flexibility activated R_k^{act} depending on frequency deviation. The flexibility activation payment C_k^{act} based on the activation price π_k^{act} is given as:

$$R_k^{act} = \begin{cases} R_k^{commit}, & \text{if } |\Delta f_k| \geq 0.1\text{Hz} \\ R_k^{commit} \cdot \frac{|\Delta f_k|}{0.1}, & \text{if } |\Delta f_k| < 0.1\text{Hz} \end{cases} \quad (6)$$

$$C_k^{act} = \pi_k^{act} \cdot R_k^{act} \quad (7)$$

This approach respects the proportionality principle of FCR-N activations, where only partial flexibility is dispatched when frequency deviation is below ± 0.1 Hz.

As BRP also serves as an FCR-N aggregator, The deployment of local flexibility alters the observed metered load L_k^{meter} , as flexibility activation either increases or decreases net consumption. When the activation is upward (frequency below 50 Hz), flexible loads reduce consumption; when downward (frequency above 50 Hz), they increase consumption.

$$L_k^{meter} = L_k \pm R_k^{act} \quad (8)$$

This affects the new imbalance value, depending on regulation direction.

$$\Delta_k^{adj} = L_k^{meter} - F_k \quad (9)$$

Thus, while providing balancing services generates revenue, it may also introduce new imbalance penalties for BRP if not coordinated effectively. The total profit P_k at each interval becomes:

$$P_k = -C_k^{imb,adj} + C_k^{cap} + C_k^{act} \quad (10)$$

Where, $C_k^{imb,adj}$ is the imbalance cost recalculated using Δ_k^{adj} . The optimization model therefore resolves a trade-off between flexibility monetization and its induced impact on BRP-level imbalances.

To effectively handle this trade-off, the integrated MILP framework solves three distinct operational scenarios for comparison. These scenarios are structured to evaluate the impact of different strategies for utilizing flexibility on overall BRP performance, balancing cost mitigation, and FCR-N revenue generation. In all scenarios, flexibility is treated as symmetrical and fully available for each ISP, as the focus lies in strategic allocation and dispatch of aggregated flexibility at the portfolio level. In the first scenario (Baseline), the BRP does not utilize any available flexibility. The objective function for this scenario is defined as:

$$\min \sum_{k=1}^N C_k^{imb} \quad (11)$$

This serves as the benchmark scenario where the BRP absorbs all imbalance penalties without deploying or monetizing any flexibility. The second scenario involves dispatching available flexibility exclusively for reducing imbalance costs. The flexibility is deployed only up to the extent of the imbalance volume in each ISP, with the goal of minimizing the adjusted imbalance cost:

$$\min \sum_{k=1}^N C_k^{imb,adj} \quad (12)$$

where, the model adjusts the imbalance volume based on the applied flexibility R_k , constrained by the maximum available flexibility in that interval.

$$\Delta_k^{adj} = \begin{cases} \Delta_k - \min(\Delta_k, R_k), & \text{if } \Delta_k \geq 0.1 \\ \Delta_k + \min(\Delta_k, R_k), & \text{if } \Delta_k < 0.1 \end{cases} \quad (13)$$

The third scenario considers the full participation of the BRP in the FCR-N market, where flexibility is committed as reserve and activated in response to frequency deviations. In this case, the BRP earns both capacity and activation payments, but the activation affects the actual load observed at the meter and thereby modifies the imbalance exposure.

$$\max_{R_k, U_k, y_k} \sum_{k=1}^N (-C_k^{imb,adj} + C_k^{cap} + C_k^{act}) \quad (14)$$

where, The binary variable U_k ensures flexibility is committed only when thresholds are met, while $y_k \in \{0,1\}$ handles activation events where required.

This scenario reveals how flexibility can be leveraged as a market resource, not only for internal cost mitigation but also as an externally valued asset, provided the system operator's

criteria are met. By quantifying both economic benefits and systemic risks of flexibility deployment, this scenario offers a holistic valuation of demand-side flexibility in modern energy markets.

III. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed optimization framework, a comprehensive case study is conducted using real-world energy market data from the Finnish power system operator Fingrid. The community load and flexibility datasets are derived from the Pecan Street database, which includes appliance-level data from over 100 households. Flexibility quantification for shiftable appliances, BESS, and HVAC systems was conducted in our prior work and forms the foundation of this study's flexibility provision layer [11], [15]. The simulation environment emulates a 24-hour operational horizon with a 15-minute resolution, corresponding to the ISPs applied in Nordic balancing markets. Each data stream is made aligned to the appropriate operational clock: the day-ahead schedule is traded and settled in hourly blocks (24×1 h), whereas both the imbalance ledger and FCR-N are decided in discrete 15-minute intervals. Consequently, every hourly day-ahead value is replicated to the four constituent ISPs, while all sub-hour data (load, flexibility, frequency) are preserved at native 15-minute resolution.

The BRP forecasts load based on historical patterns and procures energy from the day-ahead market, incurring costs based on forecasted quantities. The XGBoost model is trained on prior consumption profiles to generate accurate short-term load forecasts, achieving improved granularity at 15-minute intervals. Fig. 2 shows the actual community load and the forecasted load profile over the 24-hour horizon, along with the corresponding day-ahead market clearing prices used to calculate the energy procurement costs. The total available pre-computed symmetrical flexibility at 15-minute resolution for the entire operational horizon is illustrated in Fig. 3.

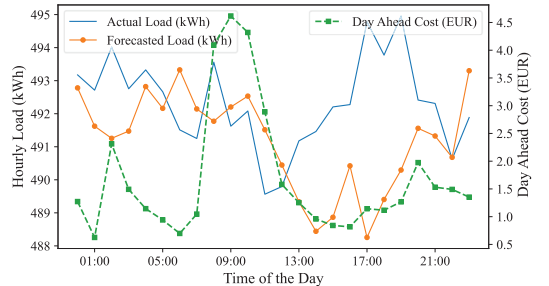


Fig. 2. Comparison of actual and forecasted load profiles alongside corresponding day-ahead energy procurement costs.

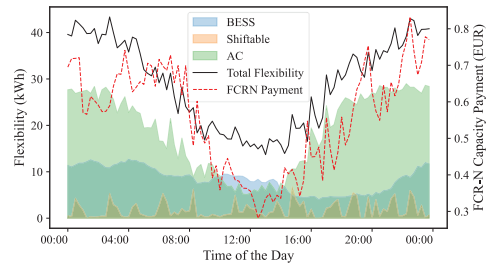


Fig. 3. Aggregated available flexibility from BESS, shiftable appliances, and HVAC systems over a 24-hour period.

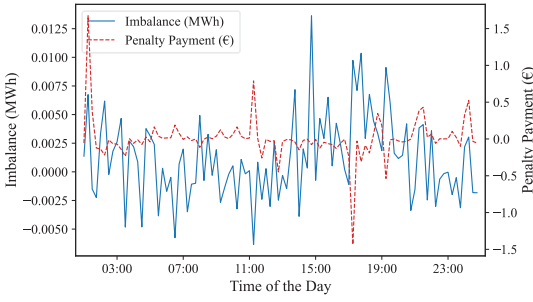


Fig. 4. Imbalance and corresponding penalty payments over each 15-minute interval under the baseline scenario.

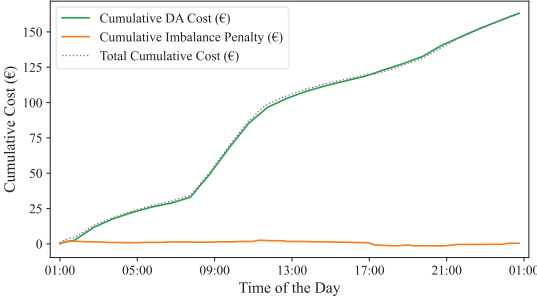


Fig. 5. Cost breakdown showing total day-ahead procurement cost and total imbalance penalty cost for the baseline scenario

Three scenarios are simulated to assess the performance of the BRP under different flexibility utilization strategies. In the baseline scenario, the BRP relies solely on day-ahead forecasts and faces penalties for real-time deviations. The imbalance volume is priced using imbalance settlement prices provided by Fingrid. Fig. 4 displays the time series of these imbalances and associated penalty payments over the entire horizon. The cumulative cost in this case reached €160.55, as depicted in Fig. 5, where energy procurement and imbalance penalties are shown separately.

In the second scenario, the BRP deploys the available flexibility to minimize imbalance penalties. Since the same 15-minute cadence applies to both settlement and flexibility activation, forecast deviations are compensated in real-time using aggregated flexibility resources. In the third scenario, the BRP additionally assumes the role of an FCR-N aggregator. In this mode, pre-quantified flexibility is reserved for frequency regulation services. Fig. 6 visualizes the cumulative cost comparison under all three scenarios, showing a clear improvement of joint BRP-aggregator strategy over the previous two modes.

Fig. 7 presents the comparison of baseline and post-FCR activation residual imbalances over a 24-hour period at 15-minute resolution. The baseline residual represents the deviation between actual and forecasted load without flexibility intervention. The post-FCR residual accounts for the effect of frequency-based symmetrical flexibility activation.

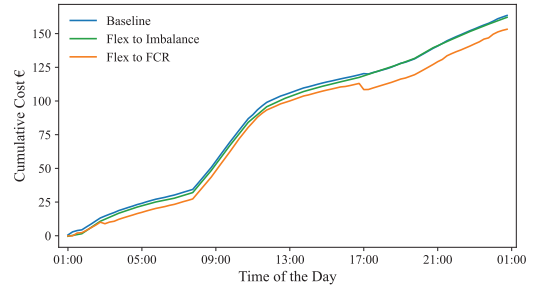


Fig. 6. Cumulative cost comparison under all three scenarios.

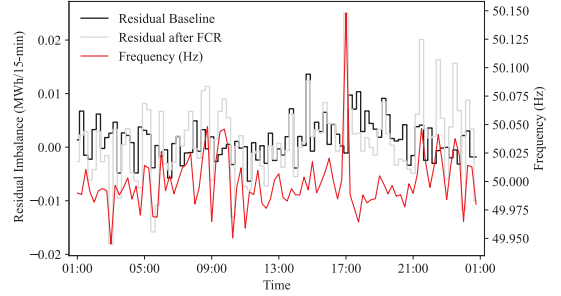


Fig. 7. Residual imbalances before and after FCR-N flexibility activation based on frequency-responsive control.

Table I provides a comparative overview of the key performance outcomes under the three optimization scenarios evaluated in this study. with a reasonable trade-off between scalability and accuracy. The proposed integrated approach leads to the most significant improvement, reducing the BRP's net operational cost by 4.75% compared to the baseline.

This case study confirms that when flexibility is jointly optimized for market participation and system balancing, substantial economic gains can be achieved. Importantly, it also highlights the necessity of properly synchronizing different market timescales. Day-ahead procurement is made on an hourly basis, while FCR-N commitments and imbalance resolutions operate at 15-minute resolutions.

TABLE I. COMPARISON OF NET OPERATIONAL COSTS UNDER THREE OPTIMIZATION SCENARIOS.

Metric	Scenario 1	Scenario 2	Scenario 3
Net Operational Cost (EUR)	163.50	162.81	155.73
% Cost Reduction vs. Baseline	0	0.41	4.75

IV. CONCLUSION

This research presents an integrated MILP-based framework for optimizing the dual-role operations of a balance responsible party that also functions as an aggregator for FCR-N. By coordinating community-level residential flexibility resources, the proposed methodology strategically minimizes imbalance costs. The comparative analysis across three distinct operational scenarios reveals that committing flexibility to the FCR-N market yields significant economic advantages, achieving 4.75% cost reduction relative to the baseline scenario. These gains primarily arise from capacity and activation payments, despite the trade-off of increased imbalance risk due to frequency-driven activations.

Importantly, this study highlights how flexibility deployed for grid services can reshape local load profiles and influence imbalance settlements, underscoring the necessity for coordinated control strategies to balance profitability with system stability. No intraday trade analysis is performed in the current study to maintain focus on optimizing local flexibility allocation and isolating the cost–benefit dynamics of reserve participation.

Future work will focus on incorporating real-time operational constraints, such as response delays and ramp rates, to more accurately model the behavior of flexible resources. Flexibility quantification will be refined by allowing asymmetric bids, offering a more granular and realistic representation of available services. The framework will be extended with robust optimization approaches to account for uncertainty in frequency deviations and market prices.

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Appendix 9

Publication X

A. Shahid, A. Rosin, R. Ahmadiyahangar, T. Korotko, and N. Shabbir, "Forecast-Driven aggregation and Real-Time coordination of Demand-Side flexibility for balancing market participation," IEEE Access, vol. 14, pp. 107225–107241, Jan. 2026, doi: 10.1109/access.2026.3711805.

Forecast-Driven Aggregation and Real-Time Coordination of Demand-Side Flexibility for Balancing Market Participation

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ABSTRACT Residential aggregators remain underrepresented in fast-acting balancing services, such as Frequency Containment Reserve for Normal operation (FCR-N), due to behavior-dependent flexibility, challenges in accurate forecasting with limited target-domain data, heterogeneous portfolio coordination, and stringent dynamic requirements for real-time delivery. This paper presents a forecast-driven aggregation and real-time coordination framework, facilitating residential aggregators participation in the FCR-N market. A transfer learning-based multi-input multi-feature neural network (MIMF-NN) is developed to generalize from representative households, enabling community-level flexibility forecasting. This flexibility is further optimized through mixed-integer linear programming (MILP) to identify market-compliant participation windows, accounting for device dynamics by mapping dynamically deliverable capacity. To effectively allocate commitments among individual households, a risk-aware hierarchical disaggregation strategy is employed, utilizing availability-weighted driver–energy quantiles and CVaR-lite caps. Upon activation within the 15-minute FCR-N interval, real-time forecast–delivery mismatches are addressed through MILP-based coordination, leveraging updated resource-availability signals. The framework is validated using a real-time digital simulator (RTDS) with the IEEE 9-bus testbed system, demonstrating compliance with FCR-N dynamic performance requirements. Numerical results indicate that MIMF-NN achieves an NRMSE of 0.092 and an R^2 of 0.925 under high comfort disturbance. During RTDS-based FCR-N activation, the aggregator delivered 2.10 kWh against a requirement of 2.03 kWh, resulting in a mean coverage ratio of 1.033 and a mean absolute tracking error of 1.74 kW, thereby demonstrating the practical viability of the proposed framework for reliable balancing market participation.

INDEX TERMS Balancing market, demand-side flexibility, energy management, flexibility aggregation, forecasting, frequency regulation, RTDS

NOMENCLATURE

Symbol	Meaning
a, i, C, k	Appliance class, household, comfort cluster, Droop coefficient (kW/Hz)
$\hat{y}_{\text{low}}, \hat{y}_{\text{high}}$	Forecasted community flexibility under C_1 and C_2 (kW)
$\bar{P}_d, \bar{P}_d, P_d$	Steady-state forecast, dynamic deliverable cap, scheduled contribution (kW)
$P_{\text{req}}, P_{\text{steady}}, P_{\text{agg}}$	Contracted reserve, droop target, delivered aggregate response (kW)
$p_{i,b}, q_{i,b}^{(\alpha)}, t_{i,b}^{(\alpha)}$	Smoothed availability probability, α -quantile, conditional lower-tail mean
$u_{i,b}^{(\alpha,\lambda)}$	CVaR-lite cap (kWh)
$\alpha, \beta, \lambda, \eta, \delta$	Disaggregation risk/weighting hyperparameters (quantile threshold, intermittency penalty, comfort penalty, availability scaling, insurance factor)

I. INTRODUCTION

The global energy landscape is undergoing a profound transformation, driven by the imperative to decarbonize and the rapid integration of renewable energy sources (RES) [1]. While RES are essential for a sustainable future, their variability and weather dependency introduce significant challenges to power system operation, primarily by increasing net-load volatility and reducing the inherent system inertia traditionally provided by synchronous generators [2]. This paradigm shift has intensified the demand for fast-acting balancing services, such as frequency containment reserves (FCR), which are essential for maintaining the supply-demand balance and keeping the system frequency within strict operational limits [3].

In this context, demand-side flexibility (DSF), the capability of electrical loads to modulate their power consumption in response to market signals or grid conditions, has emerged as a promising, cost-effective, and low-carbon resource for ancillary services [4], [5]. The residential sector represents a vast and largely untapped resource of such flexibility, housed in assets like heating, ventilation, and air conditioning (HVAC) systems, battery energy storage systems (BESS), and shiftable appliances (e.g., EV, dishwashers) [6],[7]. However, the potential of residential DSF remains critically underutilized in balancing markets. Despite a 7.3% annual growth in U.S. residential demand response capacity, its participation in ancillary service markets is minimal, a trend mirrored in European markets [8], [9]. The primary challenges are the small capacity and heterogeneity of households, which limit direct market participation, and stringent technical requirements of balancing products like the frequency containment reserve for normal operation (FCR-N) [10], [11].

To overcome these barriers, the aggregator business model has gained prominence, pooling the flexibility of numerous end-users to act as a single, sizable market entity [12]. Policy initiatives, notably the European Union's Clean Energy Package, have begun to formalize this role, recognizing "independent aggregators" and encouraging explicit demand response among small consumers [13]. The Nordic FCR-N market, for instance, procures symmetrical balancing capacity in 15-minute intervals, requiring full activation within minutes of a frequency deviation and adherence to a near-linear power-frequency response curve [14], [15]. While a non-negligible share of prequalified FCR capacity is now provided by distributed energy resources (DERs) in some regions [16], large-scale generators, industrial loads, and dedicated storage remain the dominant providers. Residential aggregators continue to face formidable obstacles, including minimum bid sizes, the need for portfolio-level performance verification, and the fundamental technical challenge of coordinating many small, diverse devices with limited telemetry and uncertain availability [17].

Existing research demonstrated the theoretical viability of

DERs for frequency regulation. Studies have optimized hybrid building energy systems with heat pumps, thermal storage, and photovoltaics [18] and hybrid power plants [19] for participation in reserve markets, focusing on storage sizing and the trade-off between turbine stress and reserve revenues. At the appliance level, thermostatically controlled loads (TCLs) have been modeled as virtual batteries for ancillary services [6], [7]. For example, probabilistic virtual battery models have been used to predict aggregated TCL flexibility for bidding into balancing markets [20]. Similarly, optimization frameworks have been developed for BESS participation in multi-FCR markets, achieving 29% reductions in aging costs [21]. These studies generally focus on single asset types, assume relatively homogeneous portfolios, or emphasize offline bidding and sizing rather than end-to-end coordination of heterogeneous residential resources under actual FCR-N product definitions.

This gap is further exacerbated by the complexities of DSF forecasting. Unlike standard load forecasting, predicting available flexibility must account for exogenous factors (e.g., weather, prices), limited data availability, user behavior, device-level constraints, and baseline definitions [22]. While data-driven approaches, from artificial neural networks [23] to LSTM-based architectures [24] and hybrid models like KA-N-HITS [25], [26], have shown promise in capturing nonlinear seasonal patterns for demand response portfolios, they are often designed for day-ahead energy markets or specific device classes like TCLs [27], [28]. Consequently, aggregators struggle to obtain robust, community-level flexibility forecasts that are both accurate and incorporate the uncertainty of resource activation on user comfort, which is crucial for reliable FCR-N bidding.

Finally, the translation of forecasted flexibility into delivered energy requires well-structured coordination, as aggregators must aggregate uncertain flexibility into market-compliant bids and then disaggregate those commitments back to individual devices. Existing frameworks for flexibility aggregation and disaggregation, such as PyFlexAD-Minkowski sums approximations [11], provide valuable foundations on DSF management. Hierarchical frameworks, such as two-level optimization schemes for EV charging in integrated MV/LV networks [29] and submodular, two-stage dynamic aggregation strategies for flexible resources [30], demonstrate scalable, user-centric coordination. Table I compares the proposed methodology with existing demand-side flexibility frameworks.

The current literature predominantly focuses on forecast-optimize-disaggregate pipelines; however, the effective participation of residential portfolios in FCR-N remains constrained by interconnected challenges. These include the behavior-dependent nature of flexibility, the necessity for reserve commitments to be dynamically deliverable within stringent activation timelines rather than solely being forecastable in a steady state, and the limited availability of target-domain data.

TABLE 1.
COMPARISON OF THE PROPOSED FRAMEWORK WITH EXISTING DEMAND-SIDE FLEXIBILITY APPROACHES

Ref.	Multi-Asset Support	Flexibility Forecasting	Risk-aware Disaggregation	Validation	Key Limitations for FCR-N Participation
[31]	General	Probabilistic estimation	No	Historical data	Probabilistic estimation without comfort modeling or dynamic response constraints; no risk-aware disaggregation or real-time coordination.
[32]	General	Scenario-based stochastic	No	Simulation	Scenario-based stochastic approach lacks device-level dynamics, comfort zones, risk-aware allocation, and real-time delivery loop.
[33]	Generic resources	No	No	Simulation	No flexibility forecasting, comfort modeling, response dynamics, or disaggregation; limited real-time coordination.
[34]	General	No	Limited (Direct scheduling of DERs).	Simulation	No forecasting or comfort modeling; direct DER scheduling without risk-aware disaggregation; limited real-time control loop.
This paper	HVAC+BESS+ shiftables	Transfer learning-based MIMF-NN forecasts	CVaR-lite + quantile weighting and eligibility gating.	RTDS with IEEE 9-bus system for dynamic grid performance	Addressed: Transfer learning-based MIMF-NN forecasts, dual-zone comfort with penalty λ , first-/second-order dynamics with dynamic caps, CVaR-lite + quantile-based risk-aware disaggregation, MILP-based closed-loop real-time coordination.

Furthermore, household-level intermittency can lead to under-delivery issues when aggregated bids are allocated to volatile devices without device dynamics consideration. Existing methodologies are primarily accessed in an offline context, focusing on congestion management or generic energy products. Forecasting models are typically trained on aggregated data without accounting for behavioral heterogeneity, leading to poor generalization when consumption patterns shift. Additionally, disaggregation strategies often apply proportional or uniform allocation mechanisms without explicit risk quantification for intermittent resources, causing systematic under-delivery. The disconnect between day-ahead planning and real-time execution leads to regulatory non-compliance and financial penalties.

To address these operational gaps, this paper introduces a forecast-driven framework aimed at the aggregation and real-time coordination of residential demand-side flexibility for effective participation in the FCR-N market.

The framework encompasses three key components: firstly, the application of transfer learning from representative households to capture behavioral diversity without necessitating complete community telemetry; secondly, the implementation of dynamic capability mapping that translates steady-state forecasts into deliverable caps compliant with FCR-N requirements; and thirdly, the establishment of risk-aware hierarchical disaggregation utilizing CVaR-lite caps and eligibility gating. The framework is validated using RTDS, implementing the IEEE 9-bus system as a dynamic testbed. This setup enables comprehensive evaluation of market compliance and the real-time dynamic performance under grid-realistic frequency variations.

The main contributions of this work are:

- 1) A transfer learning-based multi-input multi-feature neural network (TL-MIMF-NN) model is developed to

generalize from representative households and forecast community-level flexibility under low and high comfort disturbance levels from heterogeneous residential resources.

- 2) A two-stage MILP formulation is proposed that selects market-compliant participation windows by leveraging forecasted flexibility, user comfort constraints, and device dynamics through a dynamic cap mechanism. Furthermore, it performs real-time resource coordination to satisfy FCR-N activation requirements
- 3) A risk-aware hierarchical disaggregation strategy is introduced, employing transfer learning-based behavioral clusters to effectively allocate aggregated flexibility to individual households. The strategy utilizes availability-weighted lower quantiles of driver energy, incorporates eligibility gating to exclude inactive resources, alongside Conditional Value-at-Risk (CVaR) lite caps to prevent over-assignment of flexibility to volatile devices.

The novelty of this work is not the isolated use of neural forecasting, MILP, or hierarchical allocation, which are established tools, but their coupling into an operational chain tailored to the Nordic FCR-N product. Compared with prior flexibility aggregation studies, the proposed framework explicitly connects four elements that are usually treated separately: (i) transfer learning (TL-MIMF-NN with PCA+K-means) from behaviorally representative households when full community telemetry is unavailable; (ii) conversion of steady-state flexibility forecasts into dynamically deliverable capacity using 60 s and 180 s activation constraints; (iii) risk-aware disaggregation (CVaR-lite caps with adaptive quantiles) that limits assignments to volatile or intermittently available devices; and (iv) RTDS-based closed-loop validation against grid-frequency dynamics rather than offline energy-only simulation. From these four connectors, the specific designs

of the TL-MIMF-NN, dynamic capability mapping, and CVaR-lite disaggregation are novel adaptations, while the MILP scheduling and droop-based real-time control are used in a new operational context.

The remainder of this paper is organized as follows. Section II details the proposed methodology, including flexibility quantification, transfer learning-based MIMF-NN forecasting, MILP-based market participation optimization, hierarchical disaggregation, and real-time coordination architecture. Section III presents the case study setup and evaluates the performance of the proposed framework on the RTDS-based IEEE 9-bus test system. Section IV concludes the paper.

II. METHODOLOGY

This section details the proposed framework for enabling a residential aggregator to participate in the FCR-N market, as shown in Fig. 1. The integrated approach includes four key stages: forecasting community-level flexibility, optimizing market participation bids, disaggregating the bid to individual households, and real-time coordination to deliver the committed flexible power.

A. SYSTEM ARCHITECTURE

The framework is architected around the technical specifications of the Nordic FCR-N balancing market product. This market procures symmetrical upward and downward capacity in 15-minute intervals with a minimum bid of 0.1 MW. A ± 0.1 Hz frequency deviation must trigger full activation of the contracted capacity, with at least 63% of the power delivered within 60 seconds and 95% within 180 seconds. Steady-state deviations between -5% and

$+20\%$ of the contracted power are tolerated.

The aggregator controls a portfolio of residential HVAC systems, BESS units, and shiftable appliances (SA). Flexibility is characterized by two comfort disturbance levels: a low-disturbance level (C_1), where wider comfort bands are maintained and consequently more flexibility is available, and a high-disturbance level (C_2), where narrow comfort bands are available, allowing less flexibility to be offered. Appliance-level flexibility profiles are obtained using the data-driven quantification approach from our previous work, which embeds dynamic comfort zones and technical constraints into device-specific flexibility envelopes [7].

B. FORECAST-DRIVEN FLEXIBILITY AGGREGATION

Due to the distinct operational characteristics and response behaviors of flexibility resources, a resource-specific aggregation approach is employed to effectively capture the inherent heterogeneity of the residential portfolio.

A transfer learning-based MIMF-NN is used to forecast day-ahead community-level upward and downward flexibility separately for C_1 and C_2 . Fig. 2 outlines the Transfer learning architecture used to generalize from representative households to the full community. The architecture is designed to represent the multi-scale exogenous drivers of residential flexibility, daily occupancy, weekly patterns, and monthly weather, by dedicating a separate input branch to each rhythm, thereby reducing the learning burden compared to a single-stream LSTM or a hierarchical decomposition that operates only on the target series.

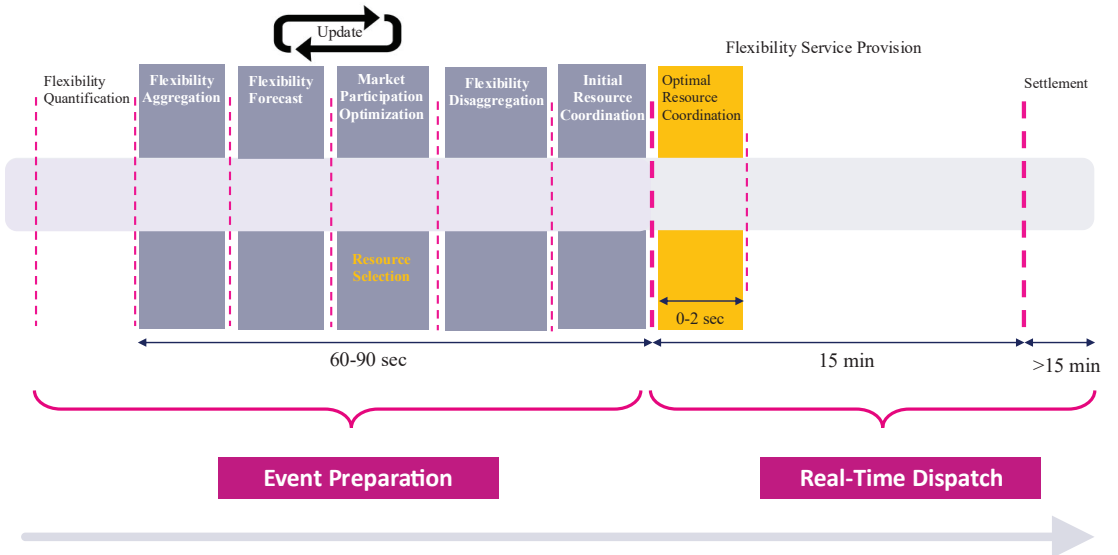


FIGURE 1. Operational workflow of the proposed end-to-end residential aggregator strategy.

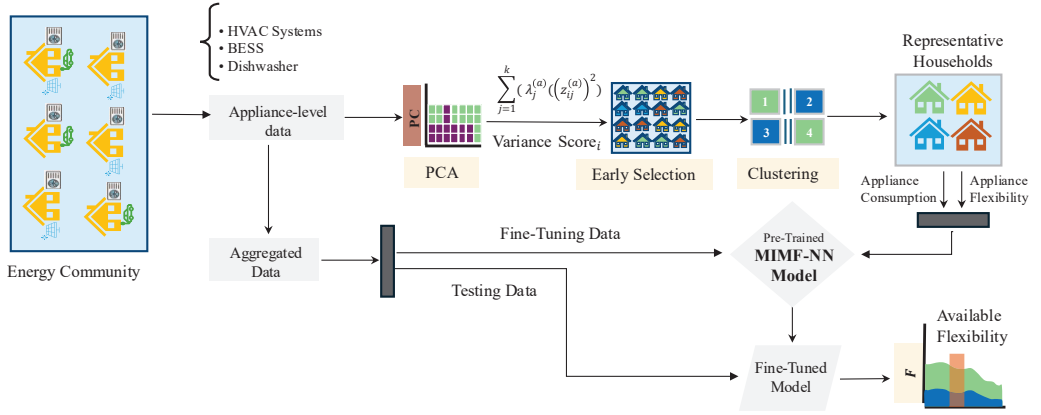


FIGURE 2. MIMF-NN-based transfer learning approach for forecasting aggregated flexibility at the community level.

1) REPRESENTATIVE HOUSEHOLD SELECTION:

To ensure the model captures the behavioral diversity of the community, a representative subset of households is selected for each appliance class a . A feature matrix $X^{(a)} \in \mathbb{R}^{n \times m}$, incorporating statistical and temporal usage patterns, is constructed for all n households. Principal component analysis (PCA) is applied to reduce dimensionality and identify dominant behavioral patterns:

$$Z^{(a)} = X^{(a)} \cdot W^{(a)} \quad (1)$$

where, $Z^{(a)}$ is the projected data along the principal components, and $W^{(a)}$ contains the eigenvectors. A variance score $V_i^{(a)}$ for each household i measures its contribution to the retained variance:

$$V_i^{(a)} = \sum_{j=1}^k (\lambda_j^{(a)} ((z_{ij}^{(a)})^2)) \quad (2)$$

where, $\lambda_j^{(a)}$ is the eigenvalue of the j^{th} principal component, $z_{ij}^{(a)}$ is the projection of the household i on that component, and k is chosen to capture nominal cumulative variance. K-means clustering is then performed on $Z^{(a)}$ to partition households into K behavioral clusters, to avoid selection bias toward dominant patterns.

$$\min_C \sum_{j=1}^K \sum_{i \in C_j} \|Z_i^{(a)} - \sigma_j\| \quad (3)$$

where, C_j is the j^{th} cluster, σ_j is its centroid. The households closest to each cluster centroid are selected, ensuring a diverse and representative training dataset for transfer learning.

Transfer learning is justified by the data-availability asymmetry, privacy-driven telemetry constraints, and strong behavioral heterogeneity faced by aggregators. Representative households provide richer source-domain behavior labels, while the full target community may only provide aggregate or sparse measurements. Pre-training learns generic appliance-use and weather-response patterns; fine-tuning then adapts these patterns to the aggregate

community. This reduces the amount of target-domain data required while preserving heterogeneity through the PCA-K-means representative selection step.

2) TRANSFER LEARNING-BASED MIMF-NN FORECASTING

After identifying representative households, a transfer learning-based MIMF-NN framework is used to scale flexibility forecasting from representative household subset to the entire residential community, as shown in Fig. 3.

For appliance class $a \in \{HVAC, BESS, Shiftable\}$, the source domain is represented as $\{X_s^{(a)}, Y_s^{(a)}\}$, where $X_s^{(a)} \in \mathbb{R}^{T \times d}$ contains input features over horizon T for representative households, and $Y_s^{(a)} \in \mathbb{R}^T$ is the corresponding flexibility profile. The MIMF-NN uses three parallel input branches for daily, weekly, and monthly feature subsets, each of which captures its respective temporal dynamics:

$$\begin{cases} X_d = \{z_t(f) \mid f \in F_d\} \\ X_w = \{z_t(f) \mid f \in F_w\} \\ X_m = \{z_t(f) \mid f \in F_m\} \end{cases} \quad (4)$$

where, F_d, F_w , and F_m are the feature sets for the respective time scales, and $z_t(f)$ is the value of feature f at time t .

Each input branch is processed by a dedicated bidirectional LSTM (Bi-LSTM) layer to learn temporal dependencies in both forward and backward directions:

$$\vec{h}_t = LSTM(X_t, \vec{h}_{t-1}), \quad \tilde{h}_t = LSTM(X_t, \tilde{h}_{t+1}) \quad (5)$$

The hidden states are refined using a multi-head attention mechanism:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (6)$$

where, Q, K, V represent query, key, and value matrices derived from Bi-LSTM outputs and d_k is the key dimension for scaling.

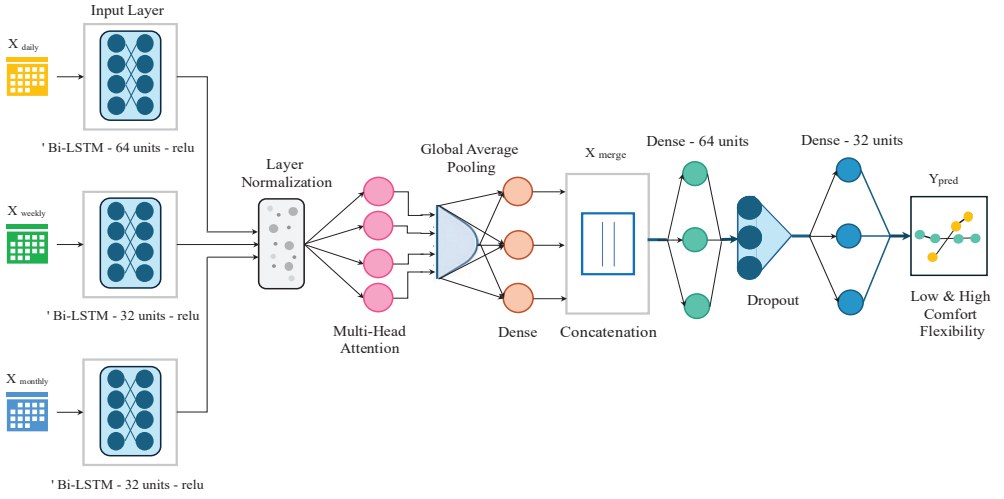


FIGURE 3. Architecture of the proposed transfer learning-based multi-input, multi-feature neural network for aggregated flexibility forecasting.

The pooled outputs from the three attention mechanisms are concatenated into a unified feature vector $[p_d, p_w, p_m]$, which is passed through a series of dense layers. The final output layer produces the joint forecasts for both comfort zones:

$$[\hat{y}_{low}, \hat{y}_{high}] = W_o \cdot \sigma(W_f \cdot [p_d, p_w, p_m] + b_f) + b_o \quad (7)$$

where W_f and b_f denote the learnable weight matrix and bias vector of the dense layer, W_o and b_o are the output layer parameters, and σ is a nonlinear activation function, ReLU.

The two outputs $\hat{y}_{low}(t)$ and $\hat{y}_{high}(t)$ represent the forecasted community-level available flexibility under the low- and high- user comfort disturbance zones C_1 and C_2 , respectively. These steady-state forecasts are subsequently converted to dynamically deliverable caps $\hat{P}_d(t)$ using equation (10), then used as inputs to the market-participation MILP as upper bounds. Specifically, $\hat{y}_{low}$ indicates resources with wider comfort bands (higher flexibility, lower user impact), and $\hat{y}_{high}$ implies resources with narrow bands (lower flexibility, higher user impact).

The model is first pre-trained on the data from the representative households (source domain) and then fine-tuned on the aggregated community-level data (target domain). The resulting forecasts for each appliance type and comfort zone are used in the market participation optimization.

End-user privacy is preserved by training the transfer learning model on anonymized, cluster-level behavioral patterns from representative households, without requiring access to individual household raw data. At the aggregator layer: household-level device traces are used locally for representative selection, model training, and disaggregation, while only aggregated bids, contracted capacity, and verified

delivery are exposed to the market operator. In a field deployment, this can be implemented with pseudonymized household identifiers, encrypted telemetry, opt-in device enrollment, and, where required, federated or edge training so that raw household traces do not leave the aggregator domain.

MIMF-NN Hyperparameters are determined via manual search on the validation set, with dropout regularization and early stopping employed to prevent overfitting and ensure optimal generalization.

C. MARKET PARTICIPATION OPTIMIZATION

The aggregated day-ahead flexibility forecasts define the maximum steady-state power that each appliance type can offer. These forecasts serve as inputs to the MILP model that determines the optimal 15-minute intervals for market participation while considering user comfort constraints. To comply with FCR-N dynamic requirements, these steady-state values are converted into dynamic feasible capabilities using first- and second-order response models.

For appliances with first-order dynamics, such as BESS, the delivered flexibility fraction after time t is given by:

$$f_{first}(t) = 1 - e^{-\frac{t}{T_b}} \quad (8)$$

where T_b is the time constant. For second-order devices, such as HVAC, the response is:

$$f_{second}(t) = 1 - (A e^{-\frac{t}{T_b}} + B e^{-\frac{t}{T_c}}) \quad (9)$$

where, $A = \frac{T_c - T_a}{T_c - T_b}$, $B = \frac{T_a - T_b}{T_c - T_b}$ and T_a, T_b, T_c are appliance-specific time constants.

An important consideration is the incorporation of device-level dynamics into linear optimization. The maximum

deliverable power $\bar{P}_d$ for each appliance d is calculated by applying dynamic caps to its steady-state flexibility forecast $\hat{P}_d$. This ensures the device can meet the FCR-N activation timelines, accounting for both physical response dynamics and communication delay τ_d :

$$\bar{P}_d = \min_{t \in \{60, 180\}} \left(\frac{f(t - \tau_d)}{\text{Target}_t} \cdot \hat{P}_d \right) \quad (10)$$

where, $\text{Target}_{60} = 0.63$ is and $\text{Target}_{180} = 0.95$ enforce FCR-N activation criteria at 60 and 180 seconds, respectively. This dynamic cap reduces steady-state forecasts to ensure that for any device, the scheduled power does not exceed what can be physically delivered within FCR-N timelines. The dynamic cap addresses a fundamental limitation of steady-state flexibility forecasts: a device may have the energy capacity to deliver flexibility over 15 minutes, but if its physical response is slow, it cannot meet the FCR-N response requirement. For example, HVAC systems cannot instantaneously deliver their full forecasted power due to thermal and actuation dynamics. Therefore, the dynamic capability mapping acts as a conservative “feasibility filter,” reducing the scheduled flexibility to a level that can realistically satisfy the 60-second and 180-second FCR-N activation requirements.

The market participation optimization problem is structured into three components: (i) decision variables representing scheduled flexibility contributions and participation indicators for each appliance class; (ii) an objective function that maximizes usable flexibility while prioritizing low-disturbance resources; and (iii) a set of constraints including dynamic capability limits, minimum FCR-N bid requirements, comfort-zone restrictions, and appliance composition rules. This structured formulation ensures that only dynamically deliverable and comfort-compliant flexibility is scheduled for market participation.

First, the dynamic deliverable cap $\bar{P}_d$ for each appliance d is pre-computed and treated as a parameter in the optimization. Second, the participation decision y_d is binary for each 15-minute interval, indicating whether appliance is scheduled to provide FCR-N capacity. Third, the minimum bid requirement P_{req} is set to 100 kW in accordance with the Nordic FCR-N product specifications. Fourth, high-disturbance (C_2) resources are limited to a fraction $\theta = 0.20$ of the total requirements to ensure user comfort is not excessively compromised. Finally, upward and downward flexibility are optimized separately using the appliance sets.

Let P_d be the scheduled contribution (kW) of appliance $d \in D$ in a 15-minute interval and $y_d \in \{0, 1\}$ be its on/off participation decision. The MILP maximizes usable flexibility while prioritizing low-disturbance resources:

$$\max_{P, y} \left(\sum_{d \in C_1} P_d + (1 - \lambda) \sum_{d \in C_2} P_d \right) \quad (11)$$

$$s.t. \quad P_d \leq y_d \cdot \bar{P}_d \quad \forall d \quad (11a)$$

$$\sum_d P_d \geq P_{req} = 100 \text{ kW} \quad (11b)$$

$$\sum_{d \in C_2} P_d \leq \theta P_{req}, \quad (11c)$$

$$\begin{cases} D_{up} = \{\text{HVAC}_{C1}, \text{HVAC}_{C2}, \text{BESS}_{C1}, \text{BESS}_{C2}\} \\ D_{down} = D_{up} \cup \{\text{SA}_{C1}, \text{SA}_{C2}\} \end{cases} \quad (11d)$$

where, $\lambda \in [0, 1]$ is a penalty factor for high-disturbance resources and $\theta = 0.20$ limits their contribution. For $\lambda = 1$, only low-disturbance capacity is preferred while smaller λ allows additional use of C_2 . The optimization follows a sequential prioritization: flexibility from C_1 is fully utilized first, and only if the requirement P_{req} cannot be satisfied, flexibility from C_2 is incrementally allocated.

The constraints are defined as follows: (11a) enforces device-specific dynamic limits, (11b) ensures the minimum FCR-N capacity requirement, (11c) limits high-disturbance contributions, and (11d) defines appliance composition for upward and downward products.

Assumptions of the MILP Formulation: (i) Device dynamics are time-invariant within each 15-minute interval; (ii) Forecast errors are independent across intervals; (iii) The dynamic cap pre-computed via Eq. (10) is a hard upper bound; (iv) High-disturbance (C_2) resources can be dispatched without additional user confirmation within the θ limit; (v) Upward and downward flexibility are optimized separately, implying no coupling constraints between them.

D. FLEXIBILITY DISAGGREGATION AND RESOURCE SELECTION

The day-ahead aggregated flexibility commitment is translated into executable household setpoints while respecting heterogeneous household behavior and intermittent device availability. Therefore, a two-stage hierarchical disaggregation strategy is employed, characterized by its behavior-awareness (using historical driver-energy patterns), uncertainty-awareness (using quantiles to bound variability), and comfort-awareness. In Stage I, flexibility is allocated to behavioral clusters, thereby stabilizing allocation ratios and minimizing variance by determining the collective potential of each cluster to deliver flexibility. Stage II makes allocations within each cluster by incorporating eligibility gating and CVaR caps, effectively mitigating the risk of under-delivery while ensuring adherence to comfort requirements.

1) STAGE I – TL-CLUSTER LEVEL ALLOCATION

Households are partitioned into behavioral clusters via PCA-K-means derived from Section II-B. For each household $i \in C_c$ and time bin b , a driver-energy signal $X_{i,b}$ (e.g., HVAC consumption, BESS SoC) is observed over a rolling K -day window ($K = 30$). Device availability is indicated by $A_{i,b} = 1\{X_{i,b} > \gamma\}$, where γ is a device-class noise floor. The Laplace-smoothed availability probability is:

$$p_{i,b} = \frac{\sum_{k=1}^K A_{i,b}[k] + a}{K + a + b}, \quad a = b = 1 \quad (12)$$

yielding $p_{i,b} \in (0,1)$ as the empirical probability of device i being available in bin b . Laplace smoothing is used because the rolling K -day availability window can be sparse for intermittent resources such as dishwashers or EV/PHEV charging. Without smoothing, a household that happened to be unavailable in the short window could receive probability zero and be permanently excluded, while a household available in every recent sample could be over-trusted with probability one. The $a=b=1$ prior keeps probabilities inside $(0,1)$ and stabilizes allocation under limited observations.

For available days ($A_{i,b} = 1$), let $q_{i,b}^{(\alpha)}$ be the α -quantile of $X_{i,b}$ conditional on $X_{i,b} > \gamma$, where α is a quantile threshold. The conditional tail mean, representing the expected value of driver-energy below this quantile threshold, is given by:

$$t_{i,b}^{(\alpha)} = \mathbb{E}[X_{i,b} | X_{i,b} \leq q_{i,b}^{(\alpha)}, X_{i,b} > \gamma] \quad (13)$$

To combine magnitude and availability within a cluster, an availability-weighted quantile mass is defined as:

$$Q_{c,b}^{(\alpha)} = \sum_{i \in c_c} (p_{i,b})^\beta q_{i,b}^{(\alpha)} \quad (14)$$

where $\beta \in [0,1]$ modulates the penalty for device intermittency. The normalized cluster participation ratio is:

$$R_{c,b}^{(\alpha)} = \frac{Q_{c,b}^{(\alpha)}}{\sum_c Q_{c,b}^{(\alpha)}} \quad (15)$$

Using these quantile-based ratios, the aggregated flexibility forecast is allocated to each TL-cluster as:

$$\hat{F}_t^{cluster} = R_{c,b(t)}^{(\alpha)} \cdot \hat{F}_t^{(low)} \quad (16)$$

Energy consistency is preserved by construction:

$$\sum_c \hat{F}_t^{cluster} = \hat{F}_t^{(low)} \quad (17)$$

2) STAGE II – HOUSEHOLD-LEVEL ALLOCATION WITHIN CLUSTERS

Within each cluster c , only active households with non-zero driver-energy are considered eligible. This eligibility gating excludes households with negligible recent activity, enhancing allocation relevance. Their quantile-based participation ratio

$$\rho_{i|c,b}^{(\alpha)} = \frac{(p_{i,b})^\beta q_{i,b}^{(\alpha)}}{\sum_{j \in A_{c,b}} (p_{j,b})^\beta q_{j,b}^{(\alpha)}} \quad (18)$$

captures both controllable magnitude and availability. A CVaR-lite cap defines a conservative upper bound on driver-energy to prevent over-assignment:

$$u_{i,b}^{(\alpha,\lambda)} = \lambda q_{i,b}^{(\alpha)} + (1 - \lambda) t_{i,b}^{(\alpha)} \quad (19)$$

where $\lambda \in [0,1]$ interpolates between the α -quantile (optimistic) and tail mean (pessimistic), providing a tunable

risk measure. A smaller λ makes the cap more robust to outliers and under-delivery.

Intuitively, CVaR-lite addresses how much flexibility can we safely assign to a household whose historical available energy varies widely? The α -quantile represents an optimistic view (e.g., 80% of days achieve at least this much energy), while the conditional tail mean represents a pessimistic view (average energy on bad days). By blending these with λ , the aggregator tunes risk tolerance: $\lambda=0$ uses only the pessimistic tail mean (most conservative), $\lambda=1$ uses only the optimistic quantile (aggressive). This avoids over-assignment to volatile devices while preserving upside when historical patterns are stable.

Classical CVaR for a loss variable is usually defined through a scenario optimization or as the expected tail loss beyond a value-at-risk threshold. Here the risk variable is deliverable driver energy, so the relevant conservative tail is the lower tail of available energy. The proposed CVaR-lite cap is a deterministic rolling-data approximation: it blends the alpha-quantile $q_{i,b}^{(\alpha)}$ with the lower-tail mean $t_{i,b}^{(\alpha)}$. It is called lite because it avoids a full scenario-based stochastic program while retaining the main operational effect of CVaR, namely limiting exposure to low-availability tail outcomes. Using low quantiles of historical driver-energy ensures that the allocated flexibility is achievable on at least 80 % of similar days, substantially reducing under-delivery risk. The household-level set-point is then calculated by applying a per-household quantile cap:

$$x_{i,t} = \min\{\rho_{i|c,b(t)}^{(\alpha)} \cdot \hat{F}_{c,t}^{cluster}, (p_{i,b(t)})^\eta u_{i,b(t)}^{(\alpha,\lambda)}\} \quad (20)$$

where, $\eta \in [0,1]$ controls the strength of availability scaling. If some caps bind, the residual cluster flexibility is redistributed among the remaining headroom to preserve $\hat{F}_{c,t}^{cluster}$. To ensure aggregate deliverability within a risk margin, α is chosen adaptively for each timestamp t such that:

$$\sum_{i \in c} (p_{i,b(t)})^\eta \cdot u_{i,b(t)}^{(\alpha,\lambda)} \geq \hat{F}_t^{(low)} \cdot (1 + \delta) \quad (21)$$

where, $\delta \in [0.02, 0.05]$ provides a safety margin aligned with the $\pm 5\%$ to $+20\%$ steady-state market deviation tolerance.

The disaggregation hyperparameters $(\alpha, \beta, \lambda, \eta, \delta)$ are selected via offline grid search on historical data, maximizing coverage while respecting shortfall and over-delivery limits. Besides dishwashers, electric vehicles (EV/PHEV) charging can also be included as a downward-flexibility resource because charging can be advanced or increased to absorb power. It changes the aggregator decision by increasing the pool of downward capacity and can reduce reliance on high-disturbance HVAC or BESS operation. However, EV/PHEV allocation is allowed only when state-of-charge, connection, departure-time, and availability conditions pass the same gating and cap logic. Without vehicle-to-grid capability, EV/PHEV resources

cannot be assumed to provide upward reserve.

E. REAL-TIME RESOURCE COORDINATION AND FCR-N DELIVERY

Following the day-ahead scheduling and disaggregation, a closed-loop real-time control system on RTDS ensures FCR-N compliance during activation, as shown in Fig. 4. RTDS acts as a source of realistic frequency deviations as well as a measurement environment for delivered FCR-N response.

During the initiation of each 15-minute market interval, the aggregator continuously measures contracted flexibility f_i^{target} per device class and the actual delivered flexibility $d_i^{act}(t)$. A single-cycle MILP optimization is employed to resolve mismatches based on resource availability:

$$\min \sum_{i=1}^n x_i \quad (22)$$

$$s.t. \quad 0 \leq x_i \leq a_i(t) - d_i^{act}(t), \forall i,$$

$$\sum_{i=1}^n x_i \geq \max(0, \sum_{i=1}^n f_i^{target} - \sum_{i=1}^n d_i^{act}(t)),$$

$$0.95 P_{steady}(t) \leq P_{agg}(t) \leq 1.20 P_{steady}(t)$$

where, x_i is the incremental flexibility adjustment for each device class, $a_i(t)$ is the currently available flexibility, $P_{agg}(t)$ is the aggregated delivered flexibility, and $P_{steady}(t)$ the droop-based steady-state request. This ensures the smallest adjustments, needed to remain within contractual bounds and FCR-N tolerances. A frequency-responsive droop control dynamically adjusts dispatched power:

$$P_{steady} = k \cdot \Delta f \quad (23)$$

The droop coefficient k is fixed within a market interval and updated only when P_{req} changes across intervals. This is necessary to maintain a constant linear droop characteristic

($P_{steady} = k \cdot \Delta f$) required by FCR-N market rules, to ensure stability of the real-time MILP coordination loop, and to keep the delivered power consistent with the interval-specific contracted capacity.

The requested real-time flexibility $\Delta P(t)$ follows a first-order exponential response droop characteristic with saturation at $\pm P_{steady}$:

$$\Delta P(t) = \begin{cases} +P_{steady} \cdot \left(1 - e^{-\frac{t}{\tau}}\right), & f \leq 49.9 \text{ Hz} \\ -P_{steady} \cdot \left(1 - e^{-\frac{t}{\tau}}\right), & f \geq 50.1 \text{ Hz} \\ k \cdot \Delta f \cdot \left(1 - e^{-\frac{-\Delta t}{\tau_{decay}}}\right), & |f - 50| \leq 0.1 \text{ Hz} \\ \Delta P_{prev} \cdot e^{-\frac{-\Delta t}{\tau_{decay}}}, & |f - 50| \leq f_{db} \end{cases} \quad (24)$$

where τ and τ_{decay} are activation and decay time constants. When the frequency leaves the deadband f_{db} , activation ramps toward P_{steady} , when it re-enters the deadband, the response decays smoothly

A droop controller converts the measured frequency deviation into the real-time aggregate FCR-N power target $P_{req}(t)$. Because HVAC and shiftable loads exhibit actuation delays and slower dynamics, the BESS compensates for the residual tracking error to ensure compliance with the aggregate target. The tracking error and BESS command are computed as:

$$e(t) = P_{req}(t) - \sum_{i \in \mathcal{A}} P_i(t) \quad (25)$$

$$s.t. \quad P_{bess}^{cmd}(t) = P_{bess}^0(t) + e(t)$$

where $P_i(t)$ is the real-time power contribution of flexible appliances i . $P_{bess}^0(t)$ is the scheduled BESS set-point from the dispatch layer, and $P_{bess}^{cmd}(t)$ is the corrected command applied in real-time.

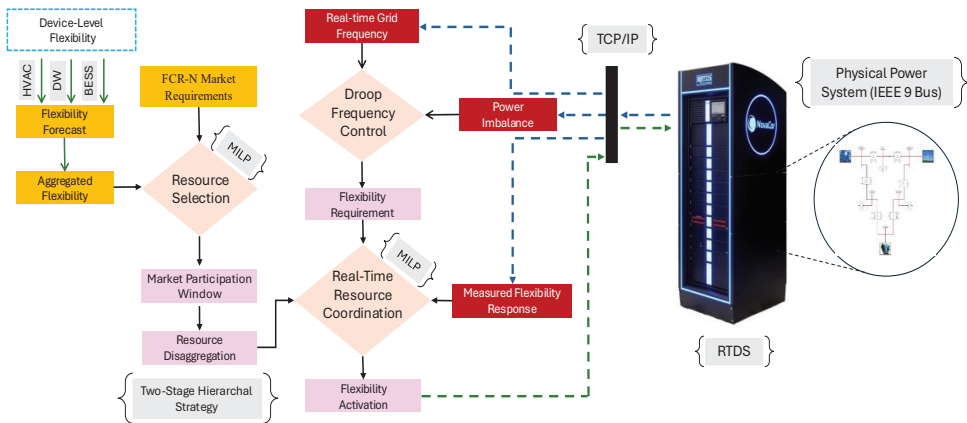


FIGURE 4. Overview of the proposed flexibility aggregation and real-time dispatch framework implemented on RTDS for FCR-N Participation

At the fleet level, this droop behavior ensures FCR-N-compliant proportional response to frequency deviations, while individual appliances follow their own calibrated dynamics. Combined with the real-time MILP, this yields a closed-loop strategy that tracks FCR-N activation trajectories while respecting device availability, comfort constraints, and market delivery tolerances

The aggregator cannot profitably bid arbitrary unavailable flexibility because bids are limited by dynamic capability caps, delivery is verified against measured response, and under-delivery is penalized through market settlement and prequalification rules. The real-time MILP uses measured availability and delivered power, so strategic over-allocation to inactive devices is corrected or rejected by the same constraints used for delivery compliance.

For replication, the implementation sequence is: build the appliance feature matrix; select representative households using PCA and K-means; pre-train the MIMF-NN on representative households; fine-tune on aggregate community data; convert forecasts to dynamic caps; solve the market-participation MILP; allocate commitments to clusters; allocate within clusters using eligibility and CVaR-lite caps; and run the real-time MILP whenever measured delivery deviates from the droop target.

From a scalability perspective, the proposed framework is designed to support larger residential portfolios through hierarchical coordination and representative learning. The transfer learning structure reduces forecasting data requirements by utilizing representative households rather than requiring full telemetry from all end users. Similarly, the two-stage disaggregation strategy performs coordination at cluster level before household-level allocation, thereby limiting optimization dimensionality growth compared to fully centralized scheduling approaches. In addition, the market-participation MILP is solved independently for each 15-minute interval using precomputed dynamic capability caps, which helps maintain computational tractability for operational deployment. As portfolio size increases, communication overhead and optimization complexity are expected to grow; however, the hierarchical aggregation structure and interval-wise decomposition are intended to mitigate this increase.

III. CASE STUDY

To validate the practical feasibility and market compliance of the proposed framework, a comprehensive case study is conducted using real-world residential data and real-time validation on an RTDS.

A. EXPERIMENTAL SETUP AND VALIDATION FRAMEWORK

The power system is modeled using the IEEE 9-bus network in RSCAD/RTDS, which provides a dynamic testbed and generates realistic grid frequency deviations. Forecasting, optimization, and control modules of the residential

aggregator are implemented in Python, with real-time communication to the RTDS established via TCP/IP. In this setup, RTDS computes the grid frequency in real-time under a representative imbalance scenario, the aggregator computes the required FCR-N activation, and the resulting aggregated power response is fed back to the RTDS as a controllable load.

Device-level flexibility profiles with a 15-minute resolution are derived from the Pecan Street and Cornwall LEM (UK) datasets. The resulting portfolio comprises 150 households (Monte Carlo-based extrapolation): 100 equipped with BESS, 50 with dishwashers (DW), and all 150 with HVAC systems. This specific resource combination is chosen to test the framework's ability to handle both dominant, predictable resources (HVAC, BESS) and intermittent, low-power loads (DW). Dynamic operating conditions, including photovoltaic and wind generation, were emulated using publicly available data from Fingrid. Table II highlights the dataset description and split strategy for the case study.

B. Transfer Learning-based Forecasting Analysis

The forecasting performance is evaluated through a multi-stage validation process. Initially, the transfer learning concept is validated by using XGBoost as a baseline model.

TABLE II
CASE STUDY DATASET DESCRIPTION AND SPLIT STRATEGY

Source	Variables used	Role	Split/usage
Pecan Street	Household/device load, HVAC, BESS, EV/PHEV charging where available	Device envelopes, representative-household training, and household-level actual energy.	Chronological 70% train, 15% validation, 15% test
Cornwall LEM (UK)	Residential demand and shiftable/charging behavior	Supplementary shiftable-load and EV/PHEV availability profiles	Same chronological split when used for forecasting
Fingrid public data	Frequency, PV, and wind-related operating traces	RTDS imbalance scenario and grid-realistic validation inputs	Scenario input, not used to train the household forecast model
Monte Carlo extrapolation	Portfolio composition and household sampling	Scaling from measured households to a 150-household aggregator portfolio	Repeated sampling for case-study construction

To validate the representative household selection process inherent in the transfer learning architect, a variance threshold is used to determine the number of principal components that capture the predominant behavioral patterns. A sensitivity analysis is performed by varying the variance threshold from 80% to 95% to assess the impact on the number of representative households and forecasting accuracy. The findings are summarized in Table III.

The analysis shows that increasing the variance threshold from 80% to 95% results in a marginal improvement in forecasting accuracy (RMSE reduces from 18.6 to 12.1) while increasing the number of representative households. Hence, the 90% threshold is selected as an optimal trade-off between representativeness and forecasting accuracy. This highlights that with just 17.3% of the residential portfolio data, the transfer learning approach captures 90% of behavioral variance.

Building on this validated threshold, three XGBoost-based strategies are benchmarked for day-ahead forecasting of aggregated HVAC flexibility: a singular model trained on community-level data, an ensemble of household-specific models, and a TL configuration where models are pre-trained on 26 representative households and fine-tuned on full-community aggregates. a TL configuration where models are pre-trained on representative households and subsequently fine-tuned using full-community aggregates.

The household-level ensemble achieved the highest accuracy under high comfort-disturbance conditions (RMSE = 6.42, $R^2 = 0.96$). However, its computational time exceeded two hour, primarily due to extensive hyperparameter tuning, thus rendering it impractical for real-time operational applications. Conversely, the single aggregated model demonstrated poor generalization (RMSE = 12.379, $R^2 = 0.708$), while the TL-XGBoost approach provided a favorable trade-off between accuracy and efficiency (RMSE = 12.302, $R^2 = 0.711$) by leveraging pre-trained models with minimal fine-tuning. Fig. 5 compares the actual and predicted aggregated HVAC flexibility for all three modelling approaches under both low and high comfort-disturbance scenarios.

TABLE III
SENSITIVITY ANALYSIS OF PCA VARIANCE THRESHOLD FOR
REPRESENTATIVE HOUSEHOLD SELECTION

Variance Threshold	Principal Components	Representative Households	RMSE
80%	3	18	18.6
85%	4	22	13.4
90%	5	26	12.3
95%	7	31	12.1

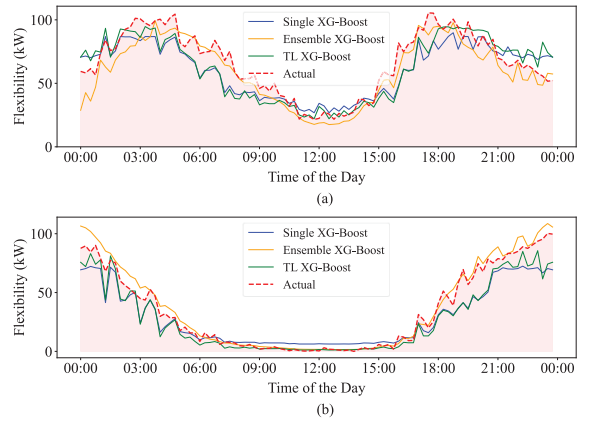


FIGURE 5. Comparison of actual vs. predicted aggregated HVAC flexibility for (a) low and (b) high comfort disturbance zones under the single-aggregate, per-household ensemble, and transfer-learning XGBoost modeling approaches.

Utilizing this validated TL concept, the proposed transfer learning-based MIMF-NN is benchmarked against a feed-forward neural network (FF-NN), transfer-learning XGBoost, and N-HITS for aggregated HVAC flexibility forecasting under both comfort zones. Transformer/TFT models were considered as recent alternatives; however, their main advantage appears in larger multi-horizon datasets with richer covariate histories, whereas the present target-domain data are sparse and behavior-driven. The comparison therefore emphasizes baselines that are implementable under the available data regime while adding a conceptual comparison to Transformer/TFT and N-HITS architectures.

The MIMF-NN employs a centralized learning approach facilitated by an Intel Core i7-12700 with NVIDIA RTX 3060 GPU, utilizing the Adam optimizer (clipnorm = 1.0). The total training time amounts to 1.56 hours, encompassing both pre-training and fine-tuning phases. The model integrates temporal features (hour, day-of-week, month) alongside occupancy, and weather features (temperature, solar irradiance) across multiple temporal scales to capture multi-horizon dependencies inherent in residential flexibility patterns.

Table IV summarizes the key hyperparameters of the proposed framework. The MIMF-NN outperforms the other models, achieving a normalized RMSE of 0.092 and an R^2 of 0.925 in the high-disturbance scenario, as highlighted in Table V.

TABLE IV
SUMMARY OF KEY FRAMEWORK HYPERPARAMETERS

Component	Hyperparameters	Value
MIMF-NN Forecasting	Daily attention heads / key dimension	4 / 32
	Weekly attention heads / key dimension	2 / 16
	Monthly attention heads / key dimension	2 / 16
	Dense layers	64, 32 (ReLU)
	Batch size	32
	Max epochs (pre-train/ fine-tune)	300/200
	Validation split	0.2
	Loss / metric	MSE / RMSE
	Early stopping patience	20
	Recurrent dropout	0.2
	L2 regularization coefficient	1×10^{-4}
	LR scheduler	ReduceLROnPlateau: factor 0.5, patience 10, min_lr 1×10^{-6}
	Learning rate (pre-train / fine-tune)	$1 \times 10^{-3} / 5 \times 10^{-4}$
Disaggregation (Grid Search)	Look-back window (K)	Recent 30 days
	Risk margin (α)	Candidates {0.2, 0.3, 0.4}; selected 0.2
	Cluster-activation threshold (λ)	Candidates {0.3, 0.5, 0.7}; selected 0.3
	Comfort scaling factor (β)	Candidates {0.3, 0.5, 0.7}; selected 0.3
	Proportionality Coefficient (η)	Candidates {0.4, 0.5, 0.8}; selected 0.5
	Device-class noise floor (γ)	HVAC/BESS: 0.05 kW; DW: 0.10 kW
	Insurance Factor (δ)	0.03 (used in the risk-margin adjustment)
Device Dynamics	HVAC: T_a, T_b, T_c, τ_d	3 s, 7 s, 12 s, 0.5 s
	BESS: T_b, τ_d	0.8 s, 0.05 s
	Shiftable Appliance: T_b, τ_d	1.2 s, 0.20 s

TABLE V
PERFORMANCE COMPARISON OF TRANSFER LEARNING-BASED FORECASTING MODELS FOR AGGREGATED HVAC FLEXIBILITY.

Model	Comfort Zone	Normalized RMSE	R ²
FF-NN	Low comfort disturbance	0.178	0.637
Proposed MIMF-NN		0.111	0.715
N-HITS		0.146	0.708
FF-NN	High comfort disturbance	0.155	0.786
Proposed MIMF-NN		0.092	0.925
N-HITS		0.104	0.891

Fig. 6 illustrates day-ahead aggregated HVAC flexibility forecasts for low and high comfort conditions.

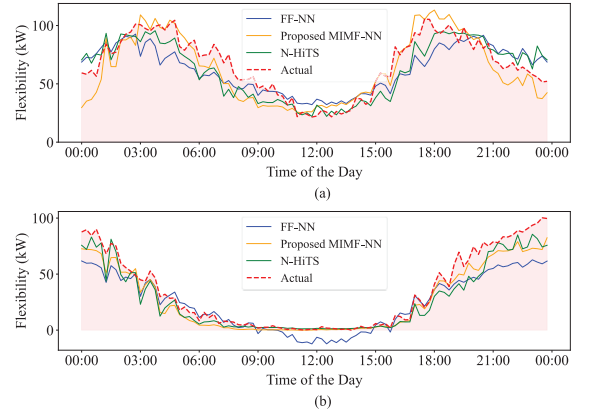


FIGURE 6. Day-ahead aggregated HVAC flexibility forecasts for (a) low and (b) high comfort disturbance zones under different TL-based models.

The MIMF-NN's advantage stems from its three-branch design: daily, weekly, and monthly rhythms are modelled separately, and multi-head attention focuses on the sparse moments when flexibility actually appears (e.g., appliance start-ups). The joint output for both comfort zones further exploits their correlation. The per-household XGBoost ensemble achieves a slightly lower RMSE (6.42 kW, R^2 0.96) but requires over two hour of hyper-parameter tuning, making it impractical for daily operation. The TL-MIMF-NN (1.56 h total training) delivers a large gain over the single-aggregate model and N-HITS while staying within an operational time budget, offering a practical accuracy-computation balance.

Transformer-based architectures (e.g., TFT) typically excel when large multi-horizon datasets with rich covariate histories are available [35], [36]. In the present setting, limited target-domain data, strong behavioral heterogeneity, and the need to preserve interpretable mapping from exogenous drivers (occupancy, weather, calendar) to flexibility, the dedicated input branches and self-attention mechanism of MIMF-NN provide a structural prior that improves sample efficiency. The transformer's self-attention mechanism would need to rediscover these temporal separations from scratch, which is data-inefficient under the available 15-month target-aggregate record. Thus, while Transformer/TFT remain valuable for larger-scale deployments, the MIMF-NN offers a more suitable accuracy-data trade-off for the realistic aggregator scenario considered here.

C. MARKET PARTICIPATION WINDOW OPTIMIZATION

The forecasted flexibility serves as input to the first-stage MILP optimization, which identified feasible 15-minute participation windows while ensuring compliance with FCR-N dynamic requirements. The optimization process incorporates device-specific response dynamics through constraints that capped deliverable power based on 60-

second and 180-second activation targets. To assess the robustness of the market participation optimization against uncertainties in device-level dynamic characteristics, a sensitivity analysis is conducted regarding the HVAC time constants (T_b, T_c), which are influenced by factors such as ambient conditions, building insulation, and occupant behavior.

The reduction in feasible 15-minute windows, as indicated in Table VI, is driven by the physical degradation of HVAC response and the comfort-aware optimization logic embedded within the MILP formulation. As the HVAC time constant increases, the dynamic cap ($\bar{P}_d$) decreases, leading to a reduction in the maximum deliverable power from low-disturbance (C_1) HVAC assets.

In order to satisfy the 100 kW FCR-N requirement (P_{req}), the optimizer is compelled to increasingly depend on flexibility derived from the high-disturbance comfort zone (C_2). However, the MILP formulation limits C_2 contributions to $\theta = 20\%$ of P_{req} to ensure user comfort is maintained. Therefore, at +20% variation, the C_1 deficit exceeds the potential compensation achieved through C_2 resources, causing a significant drop to only 10 feasible windows. Fig. 7 illustrates the aggregated flexibility optimized via MILP under both comfort zones, highlighting the specific time windows in which the aggregator meets the FCR-N requirement. This MILP-based optimization for market-participation window selection solves in approximately 0.9 seconds per run on average, making it suitable for operational day-ahead scheduling.

D. DISAGGREGATION EFFECTIVENESS AND RESOURCE ALLOCATION

The effectiveness of the proposed risk-aware hierarchical disaggregation strategy is evaluated against a proportional allocation baseline. The hyperparameters for the disaggregation framework are adjusted via an offline grid search to maximize the coverage ratio while respecting fleet shortfall constraints. Fig. 8 demonstrates the effectiveness of the first stage of the disaggregation by presenting the disaggregated BESS flexibility contributions at the cluster level. A quantitative comparison of site-level disaggregation accuracy between the proportional baseline and the proposed technique for a representative 15-minute market interval (02:30–02:45) is summarized in Table VII.

TABLE VI
SENSITIVITY OF MARKET PARTICIPATION TO HVAC TIME CONSTANT VARIATIONS.

Parameter Variation	Change in Max. Deliverable Capacity ($\bar{P}_d$)	Feasible Windows (15-min intervals /day)
Nominal Case	0%	18
HVAC (+10%)	-3.5%	17
HVAC (+15%)	-8.2%	15
HVAC (+20%)	-10.1%	12

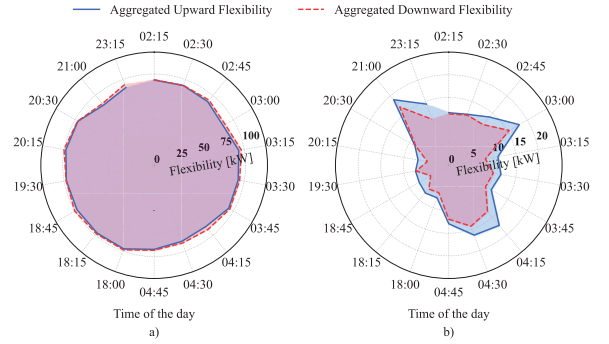


FIGURE 7. MILP-based aggregated flexibility under (a) low and (b) high comfort-disturbance zones, highlighting the time windows when the aggregator can meet FCR-N balancing-market requirements.

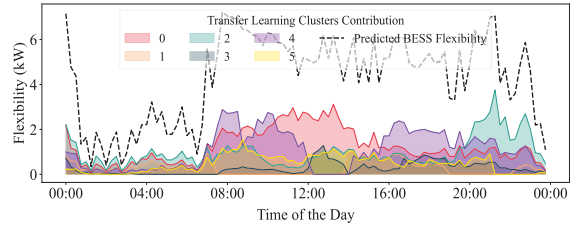


FIGURE 8. Disaggregated cluster-wise BESS flexibility contribution under high comfort disturbance zones.

Fig. 9 depicts the site-level under-delivery distribution for HVAC, BESS, and DW for the same interval. The proposed risk-aware approach significantly outperformed the baseline, reducing fleet-level shortfall by 31.6% for HVAC, 38.2% for BESS, and 48.5% for DW. The effectiveness of the proposed method in handling intermittent resources is particularly evident for dishwashers, where the shortfall is reduced from 1.03 kW to 0.53 kW.

TABLE VII
AGGREGATED REQUIRED AND DELIVERED FLEXIBILITY WITH SITE-LEVEL ERROR METRICS FOR EACH APPLIANCE, DURING A 15-MINUTE MARKET INTERVAL.

Disagg. Technique	Appliance	Required Flexibility (kW)	Delivered Flexibility (kW)	Fleet shortfall (kW)	Sites	MAE (kW)	RMSE (kW)
Proportional (Baseline)	HVAC	91.141	84.427	6.714	39	0.172	0.181
	BESS	11.119	9.027	2.091	17	0.122	0.139
	DW	2.182	1.150	1.032	13	0.079	0.086
Risk-Aware Hierarchical (Proposed)	HVAC	91.141	86.551	4.590	31	0.148	0.156
	BESS	11.119	9.827	1.292	14	0.092	0.105
	DW	2.182	1.650	0.532	11	0.048	0.052

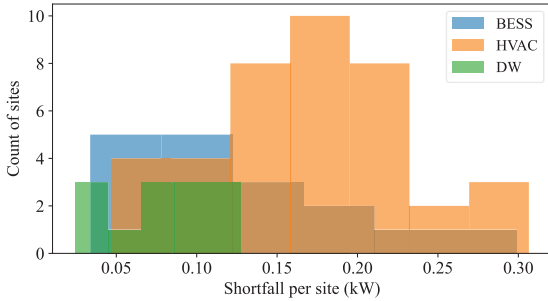


FIGURE 9. Site-level under-delivery distribution for HVAC, BESS, and DW flexibility during 15-minute market intervals (02:30-02:45).

Fig. 10 highlights disaggregated BESS flexibility at the household level. To validate household-level disaggregation quality, Fig. 11 compares actual and disaggregated flexible energy for ten representative households over the 02:00–04:59 time window, where flexible energy is defined as the integral of the 15-minute FCR-N capacity profile over time. The close alignment between actual and disaggregated energy confirms that the quantile-based scheme preserves both aggregate energy and household-level structure.

The risk-aware disaggregation accepts a small, controlled over-delivery margin (coverage ratio 1.033) in exchange for a substantial reduction in fleet shortfall—31.6 % for HVAC, 38.2 % for BESS, and 48.5 % for DW—a trade-off that is essential in FCR-N markets where under-delivery penalties outweigh the cost of marginal over-delivery.

E. REAL-TIME FCR-N COMPLIANCE AND PERFORMANCE

The end-to-end framework was validated through real-time testing on RTDS during a 280-second FCR-N activation window. The droop-based target required 2.03 kWh of total energy flexibility (mean power $\approx$ 26.1 kW), while the aggregator, using the risk-aware hierarchical disaggregation strategy, delivered 2.10 kWh, corresponding to an energy overshoot of about 0.07 kWh (3.3%) and a mean coverage ratio of 1.033.

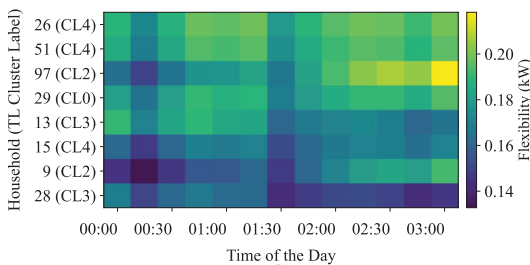


FIGURE 10. Disaggregated BESS flexibility of a few households under high comfort-disturbance zones

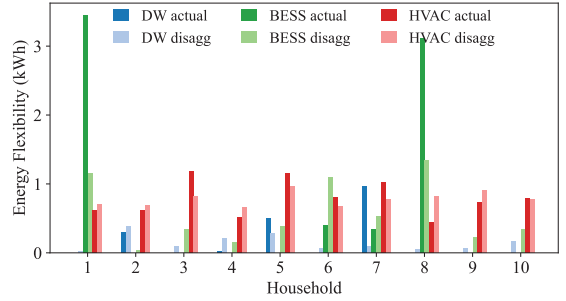


FIGURE 11. Comparison of actual and disaggregated household-level energy flexibility over the 02:00–04:59 window, obtained by integrating 15-minute FCR-N capacity profiles.

The mean absolute tracking error during this period is approximately 1.74 kW, indicating that the delivered power closely follows the droop-based target. A comparison of real-time flexibility delivery metrics for both proportional and risk-aware disaggregation strategies is summarized in Table VIII. The proposed framework corrected the upward flexibility shortfall from 7.91% to a 1.4% surplus and downward delivery from a 7.93% shortfall to a 3.4% surplus compared to the proportional baseline. Fig. 12 demonstrates the stabilizing effect on grid frequency, while Fig. 13 shows the real-time power response of individual resource types, confirming close tracking of the droop target with deviations within ± 3 kW. The real-time MILP coordination required only 0.67 seconds per interval, affirming the framework's suitability for online operation.

TABLE VIII
COMPARISON OF REAL-TIME FLEXIBILITY DELIVERY METRICS FOR PROPORTIONAL AND RISK-AWARE DISAGGREGATION TECHNIQUES ON RTDS.

Disagg. Technique	Required Energy Flexibility (kWh)		Delivered Energy Flexibility (kWh)		Coverage Ratio	MAE (kW)	RMSE (kW)
	Upward	Downward	Upward	Downward			
Proportional (Baseline)	0.139	-1.893	0.128	-1.743	0.921	3.691	7.510
Risk-Aware Hierarchical	0.139	-1.893	0.141	-1.958	1.033	1.743	3.552

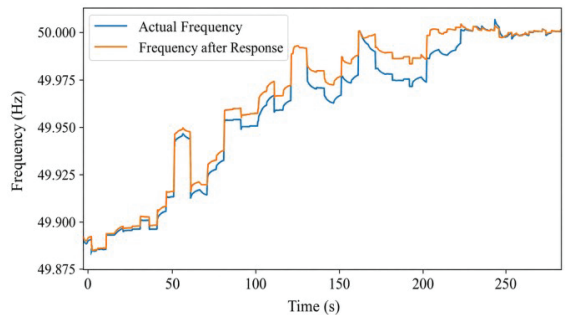


FIGURE 12. Comparison of actual grid frequency and improved frequency after flexibility response simulated on RTDS.

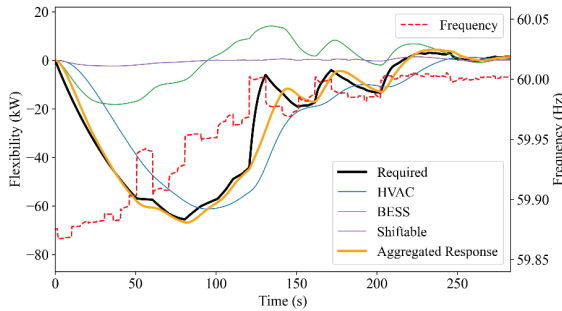


FIGURE 13. Real-time flexibility response of HVAC, BESS, and shiftable loads on RTDS to frequency deviation.

The computational results indicate that the framework is scalable for operational scheduling at the tested portfolio size: the market-participation MILP solves in approximately 0.9 s per day-ahead run and the real-time coordination MILP solves in approximately 0.67 s per interval. For larger deployments, scalability is supported by the hierarchical structure: forecasting is performed at community, disaggregation is decomposed by behavioral clusters, and real-time corrections operate on active resource classes rather than requiring a monolithic household-level stochastic optimization. In practice, larger portfolios can be handled by parallel cluster-level allocation, rolling-horizon updates, and feeder-level decomposition.

The current study has following main limitations. First, RTDS validation uses the IEEE 9-bus test system and a 150-household extrapolated portfolio, so distribution-network constraints, feeder congestion, and communication dropouts should be tested in larger field-oriented deployments. Second, device response parameters are assumed to be calibrated and stationary within an interval; real installations require online parameter updating. Third, privacy is addressed architecturally but not implemented as a full federated-learning protocol in this paper. Fourth, market behavior is represented through compliance constraints and delivery verification; strategic bidding, settlement rules, and long-term user opt-out behavior remain important extensions.

In summary, the case study confirms the technical feasibility and operational effectiveness of the proposed methodology, establishing its potential for enabling residential aggregators to effectively participate in balancing markets.

IV. CONCLUSION AND FUTURE WORK

This paper investigates the systemic underrepresentation of residential aggregators in the fast-acting balancing markets, a challenge stemming from the confluence of behavior-dependent flexibility, limited target-domain data availability, heterogeneous portfolio coordination, and stringent real-time delivery requirements. To address these interconnected challenges, a forecast-driven aggregation and real-time coordination framework is proposed, integrating three core innovations: a transfer learning-based Multi-Input Multi-

Output Feedforward Neural Network (MIMF-NN) for community-level flexibility forecasting that reduces training data requirements through representative household selection; a MILP formulation for market participation window selection that incorporates dynamic capability mapping to account for appliance response behavior and ensure Frequency Containment Reserve-Normal (FCR-N) activation compliance; and a two-stage risk-aware hierarchical disaggregation strategy for household-level flexibility allocation that utilizes Conditional Value-at-Risk (CVaR)-lite caps to address under-delivery risks from intermittent resources, complemented by a real-time coordination layer enabling droop-based responses under realistic grid dynamics.

Experimental results demonstrate that the proposed transfer learning-based MIMF-NN achieves a normalized RMSE of 0.092 and an R^2 of 0.925 for community-level flexibility under high comfort disturbance, outperforming baseline models while requiring training data from only 17% of households. The risk-aware disaggregation approach significantly enhances allocation efficiency, reducing shortfall by 31.6% for HVAC, 38.2% for BESS, and 48.5% for DW compared to proportional allocation method. Real-time digital simulator (RTDS)-based validation on an IEEE 9-bus system confirms robust framework performance, exhibiting a coverage ratio of 1.033 and a mean tracking error of 1.74 kW during FCR-N activation events.

Future research will focus on extending this framework toward scalability to larger networks configurations, expanding capability toward asymmetric and longer-duration reserve products such as manual Frequency Restoration Reserve (mFRR), and investigating federated learning architectures to enable privacy-preserving adaptive coordination across distributed aggregator networks. Extending the framework to incorporate numerical validation of EV/PHEV fleets with plug-in availability forecasting and vehicle-to-grid (V2G) capabilities remains an important direction for future research.

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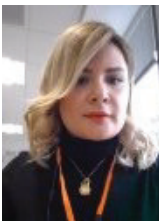
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