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A Peer-to-Peer Energy Trading Optimization for Peak Load Management in Energy Internet Systems

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***Abstract*--The convergence of widespread renewable energy sources (RES) and Internet of Things (IoT) technologies has catalyzed the development of the Energy Internet (EI), enabling advanced energy management paradigms. The EI framework facilitates the integration of numerous distributed generation units and leverages digital intelligence to enhance energy sharing, optimize grid asset utilization, and bolster overall power system security. Concurrently, rapid socio-economic growth has intensified global energy demand, leading to periodic shortages that challenge grid reliability. These scarcity conditions are predominantly manifested during peak load periods of the system. Consequently, a significant body of research is dedicated to peak load shifting and shaving to mitigate this issue. Nevertheless, few studies have systematically exploited the full capabilities of the EI framework to achieve this critical objective. This research, therefore, aims to develop and propose an EI-based optimization problem specifically designed to solve the peak load shifting problem with the primary goal of minimizing total system cost. The proposed methodology achieves this by optimizing the scheduled charging and discharging cycles of end-user Energy Storage Systems (ESS). Within this formulated problem, each prosumer—an entity that is both a consumer and a potential supplier—participates in a localized energy market. The operational cost model must comprehensively account for the costs of power sourced from the conventional grid and local RES, the storage dynamics within the ESS, and the accurate application of Real-Time Pricing (RTP) signals to all generated and consumed energy.**

***Index Terms*- Energy Internet, Energy Storage System, Peak Load Shifting, Prosumer, Real-Time Pricing.**

TABLE I
Abbreviations

Abbreviation	Full Term
EI	Energy Internet
RES	Renewable Energy Sources
IoT	Internet of Things
ESS / BESS	(Battery) Energy Storage System
DSM	Demand-Side Management
RTP	Real-Time Pricing
P2P	Peer-to-Peer
PV	Photovoltaic
PCS	Power Conversion System
BOP	Balance of Plant
MIP	Mixed-Integer Programming
SPM	Smart Polygeneration Microgrid
SEB	Smart Energy Building
PAR	Peak-to-Average Ratio

I. Introduction

THE Modern power systems stand on the brink of a historic transformation. The rapid increase in energy demand, growing environmental concerns, and the imperative to enhance reliability have created unprecedented challenges [1]. These challenges necessitate a fundamental transition from traditional, centralized, and passive generation paradigms toward the utilization of distributed and renewable resources within an integrated, intelligent system framework [2-3]. In this context, significant advancements in the IoT and renewable energy sources have catalyzed the emergence of a new paradigm: the EI [4-5].

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Within the EI framework, all components of the energy system—from large-scale generators and microgrids to end-users and distributed energy storage units—are interconnected via digital platforms [6]-[7]. This connectivity enables intelligent, integrated, and real-time management of energy production, storage, distribution, and consumption [8]. The primary goals of the EI are to increase energy utilization efficiency, facilitate the widespread and secure integration of renewables, and ultimately establish a resilient, sustainable, and efficient energy system [9]-[10]. In this transformed energy landscape, IoT technology, with its capability for large-scale, real-time data collection, processing, and exchange, serves as the backbone [11]. One of the most pressing challenges in contemporary power systems is the phenomenon of "peak load." Energy shortages, particularly during peak hours, can occur due to total demand exceeding available generation capacity, outages of generation units, or fuel shortages in conventional power plants [12]. This issue not only threatens grid reliability but also drastically increases operational costs [13]. In this regard, the "peak load shifting" strategy is recognized as an effective solution to alleviate grid stress during peak hours and enhance system stability [14]-[15].

This research aims to propose a comprehensive framework within the EI to address the peak load shifting problem. The proposed model integrates active participation from end-users (who can act as prosumers), distributed battery energy storage systems, and renewable sources, while employing a real-time pricing mechanism. Its objective is to minimize the total energy cost for consumers and optimize the charging and discharging scheduling of storage units.

Numerous studies have investigated various strategies for demand management and peak load shifting, primarily focusing on Demand-Side Management (DSM), RTP, and the deployment of BESS. The theoretical foundations and benefits of DSM have been extensively explored in the literature [16]-[17]. At the end-user level, studies such as [18] have focused on reducing energy consumption and prioritizing power scheduling to achieve load shifting. Ref. [19] has integrated residential electricity management with solar power generation units. In [20], the use of smart meters and small-scale storage units in homes encouraged users to manage their energy consumption. The development of intelligent controllers based on neural networks for coordinating distributed energy resources and household appliances represents a further step in optimizing building energy use [21].

Dynamic price signals are recognized as a key driver for modifying consumer behavior [22]. Research [23] introduced an energy system based on real-time pricing for the automatic adjustment of user consumption. Study [24] also integrated smart grids and electric vehicles using optimization models to reduce grid operational costs. Realistic demand response models have been developed for effective market interaction [25-26].

The use of BESS has also received significant attention. This includes BESS scheduling in competitive markets [27] and power management in grid-connected systems with PV and batteries [28]. For instance, [29] utilized BESS to store energy during low-load conditions and supply power during peak demand, thereby improving grid reliability. In [30], a mathematical model for BESS was presented that can smooth load variations. Considerations related to battery lifecycle characteristics have also been addressed in the optimization of isolated power systems [31]. Study [32] further demonstrated how BESS can maximize profit for its owners by storing energy during low-price periods and selling it when prices are high.

Various optimization techniques, including Artificial Intelligence [33], Evolutionary Algorithms [34-35], as well as Robust [36] and Stochastic [37-38] approaches, have been employed to manage uncertainty in power systems. These methods provide a solid foundation for developing energy management models in complex environments. Furthermore, concepts such as Networked Microgrids [39] and business models for microgrid aggregators [40] have opened new horizons for optimized energy management .As evident from the literature review, a significant research gap exists in the simultaneous integration of these three strategies (DSM, RTP, BESS) within a unified, decentralized EI framework. Most studies have focused on only one or two aspects, often overlooking the active and bidirectional role of end-users in a dynamic energy market. By addressing this gap, this paper proposes a comprehensive optimization problem where end-users can trade energy with one another and the grid within an intelligent platform influenced by real-time price signals.

While the existing body of work provides robust foundations in DSM, RTP-based mechanisms, and BESS scheduling, a critical synthesis within a fully decentralized EI framework is lacking. Studies such as [19] and [21] optimize building-level energy use with local RES but do not integrate a dynamic P2P market. Research like [27] and [32] focuses on BESS arbitrage in wholesale markets, often neglecting the proactive role of prosumers at the distribution level. Furthermore, models incorporating RTP [23]-[24] typically treat consumers as price-takers rather than proactive traders. This paper bridges these gaps by proposing a holistic optimization model that simultaneously integrates: (1) a prosumer-centric P2P energy market, (2) RTP-driven DSM, and (3) coordinated BESS scheduling—all within a unified EI architecture. The proposed formulation distinctively models the complete cost structure for prosumers (grid purchase, RES generation, ESS capital/maintenance). It enforces operational constraints based on real-time market signals, enabling a more realistic assessment of peak shaving and cost-saving potentials.

To validate the proposed optimization problem, a series of numerical simulations was conducted. The results demonstrate a significant reduction in the system's peak-to-average ratio, confirming the method's efficacy in flattening the load profile. Furthermore, the proposed energy trading mechanism among prosumers results in a measurable decrease in their aggregate electricity costs, while also enhancing the utilization rate of distributed renewable energy within the network.

The structure of this paper is as follows: Following the introduction, Section 2 provides a literature review and a precise problem statement. Section 3 is dedicated to detailing the problem formulation and the mathematical model. The simulation environment and obtained results are presented and analyzed in Section 4. Finally, Section 5 offers conclusions and suggestions for future research.

II. PROBLEM FORMULATION & MATHEMATICAL MODEL

The proposed EI framework is illustrated in Fig. 1. In this model, energy is conceptualized as a tradable commodity whose price is dynamically determined by real-time market demand. This establishes a direct correlation where peak demand periods correspond to the highest energy prices, whereas the lowest prices occur during off-peak periods.

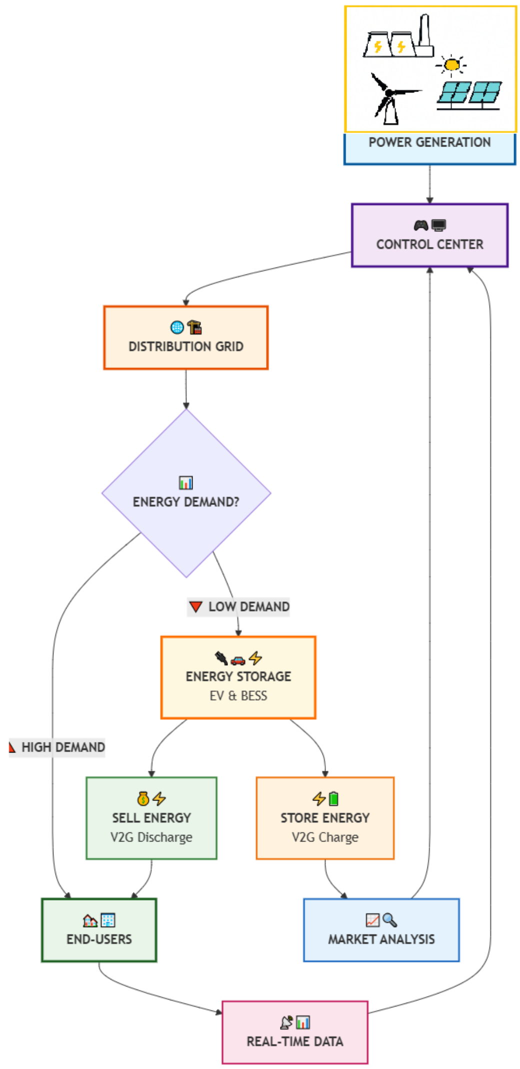


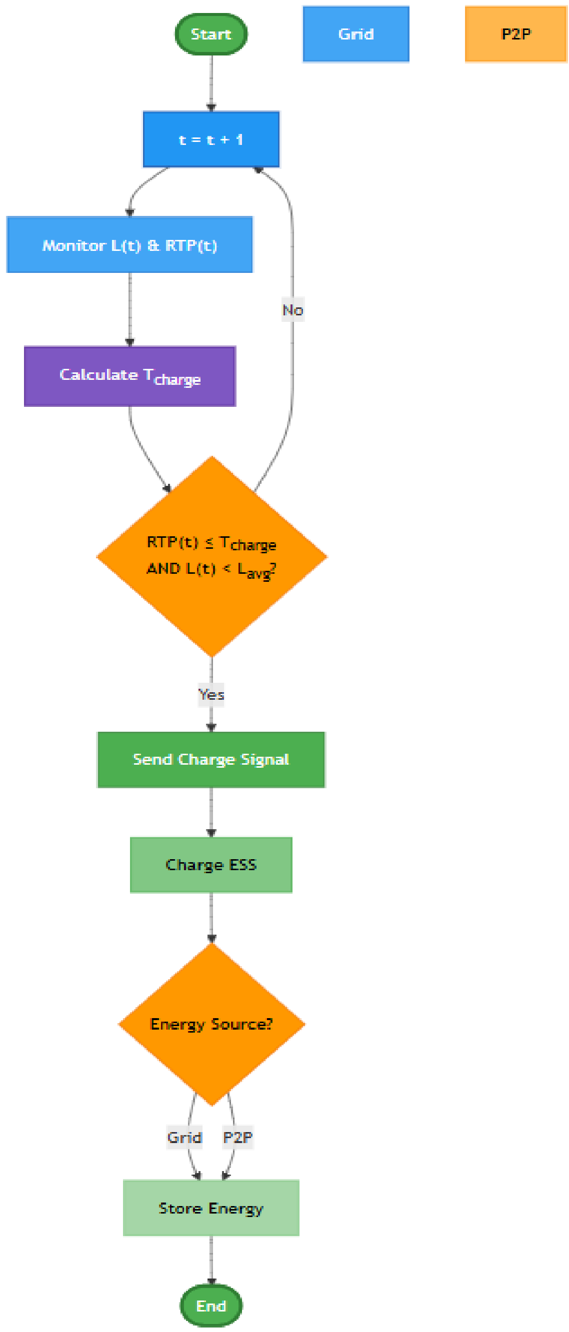
Fig 1. The EI framework

Within the EI network, user demand is accurately quantified through smart metering infrastructure, with this data transmitted to a central control center. This system enables a more realistic and granular representation of load patterns. The control center is then responsible for dispatching energy based on the aggregated requested load.

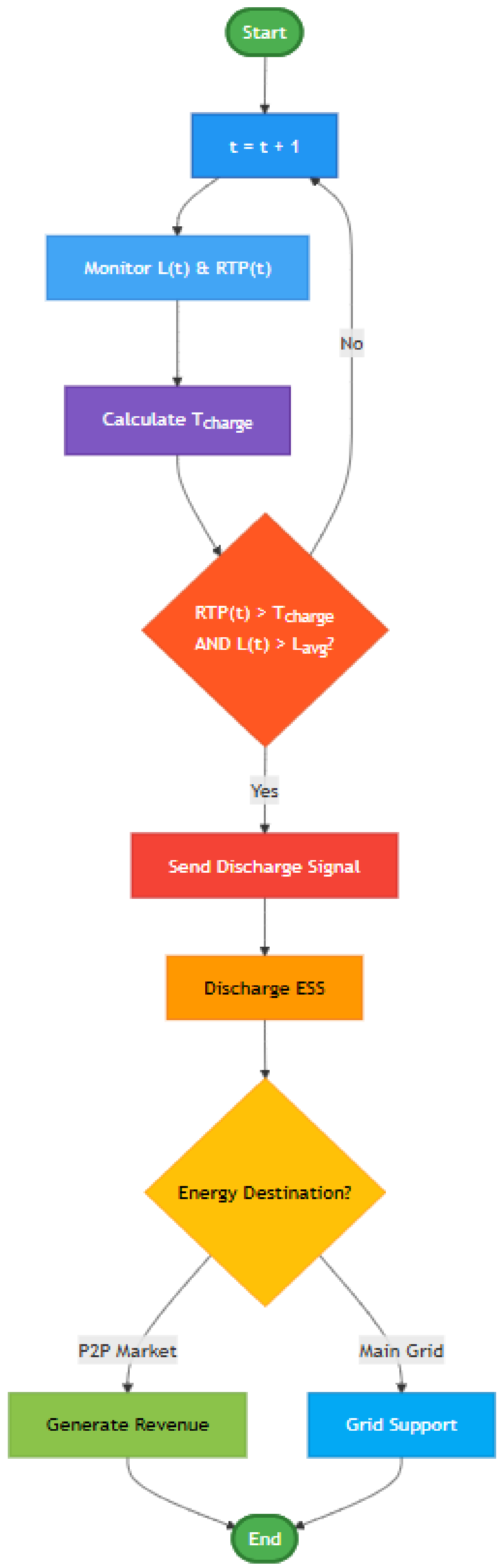
A key feature of this framework is its bidirectional communication capability. The control center's dispatch logic, detailed in Fig. 2, moves beyond simple price thresholds to incorporate both economic and grid-stability signals.

Fig. 2(a) illustrates the charging logic. The control center continuously monitors real-time load $L(t)$ and price $RTP(t)$. A charging signal is broadcast to prosumers only when two concurrent conditions are met: (1) The $RTP(t)$ is at or below a dynamic charging threshold $T_{ch}(t)$, and (2) The grid load $L(t)$ is below the daily average load $\bar{L}$. This prevents charging from exacerbating grid stress during periods of low price but high absolute demand. The primary threshold is $T_{ch}(t) = RTP^{i-1}_{min} + \gamma\Delta_{i-1}$. To ensure robustness during periods of low price volatility (e.g., $\Delta_{i-1} \approx 0$), a fallback mechanism is implemented. If Δ_{i-1} is below a defined minimum (e.g., 5% of RTP^{i-1}_{min}), the system defaults to a secondary threshold based on a rolling 7-day average RTP, maintaining system responsiveness.

Fig. 2(b) outlines the discharging logic. Discharge is triggered when the grid load $L(t)$ exceeds $\bar{L}$ and the $RTP(t)$ surpasses a dynamic discharging threshold $T_{dis}(t) = RTP^{i-1}_{min} + \beta\Delta_{i-1}$, where $\beta > \gamma$ (e.g., $\beta = 0.8$). This ensures prosumers capitalize on high prices while directly contributing to peak shaving. Upon receiving the signal, prosumers schedule energy injection from their BESS, either to the grid or to other consumers via the P2P market.



(a)



(b)

Fig 2. Decision flowcharts for the proposed energy management strategy: (a) ESS charging mode, (b) ESS discharging mode.

This section presents the mathematical formulation for the load shifting problem introduced previously. The investigation focuses on peak load management within the EI framework, incorporating a novel peer-to-peer energy market among end-users—a distinctive feature that is not comprehensively addressed in the existing literature.

The proposed model employs a comprehensive, system-wide approach that integrates the complete generation portfolio with all consumption nodes. The proposed formulation includes the base foundation, incorporating the charging dynamics of energy storage systems from renewable sources—specifically, wind and PV generation.

Furthermore, the model establishes and analyzes the synergistic relationship between the Energy Internet infrastructure and distributed energy storage resources for managing energy from the main grid, wind turbines, and solar PV installations. Table II brings all the parameters needed in this research.

TABLE II
Simulation Parameters

Parameter	Definition
C_{grid}	The total cost of energy procured from the main grid by all consumers
C_{m}	Aggregate capital and maintenance cost of consumer-owned energy storage systems
C_{res}	levelized cost of energy from consumer-owned renewable generation assets
B_{store}	A revenue stream from energy arbitrage via storage system participation in market operations.
i	Index of the day under analysis
t	Time index
$RTP_i(t)$	RTP at hour t of the ith day
$RTP_{\min}^{i-1}$	Minimum RTP on the previous day
$RTP_{\max}^{i-1}$	Maximum RTP on the previous day
Δ_{i-1}	Maximum RTP variation on the previous day
γ	Parameter indicating the peak-to-off-peak load ratio
$E_{store}^{\max}$	Maximum capacity of energy storage devices
P_{PCS}^{u}	Unit price of PCS (Power Conversion System)
P_{Store}^{u}	Unit price of energy storage
P_{BOP}^{u}	Unit price of BOP (Balance of Plant)
P	Energy capacity of PCS and BOP
C_{wind}	Cost of generated wind energy
C_{pv}	Cost of generated PV energy
E_{store}	Total energy stored in energy storage devices
μ	Charge/discharge efficiency of energy storage devices
$E_{wind,t}$	The amount of wind energy stored in the energy storage
E_{PV}	Amount of PV energy stored in the energy storage
E_{grid}	Amount of grid energy stored in the energy storage
M_{wind}	Daily maintenance cost of the wind turbine generator
M_{PV}	Daily maintenance cost per unit area of solar energy equipment
$E_L^i(t)$	Grid energy consumed by users at hour t of the ith day
$E_{ES,t}$	Grid energy used by users for charging at hour t of the ith day
Decision Variable	
$\delta_{grid,t}$	Binary parameter indicating whether a user charges using grid energy at hour t

The core objective function is formulated to minimize the total daily energy cost for all users, expressed as follows:

$$\text{Minimize} \quad C_{grid} + C_m + C_{res} - B_{store} \tag{1}$$

It is noteworthy that wind and photovoltaic generation can be either directly consumed or stored for later use. Consequently, storage systems are prohibited from grid charging during peak load intervals to prevent network congestion.

The complete optimization framework is subject to constraints defined in equations (2), (5), (6), and (9). The grid energy cost component is formulated as:

$$C_{grid} = \sum_{t=1}^{24} RTP_i(i).E_L^i(t) + \sum_{t=1}^{24} RTP_i(i).E_{ES,t}^i(t).\delta_{grid,t} \tag{2}$$

The first term represents the cost of energy directly consumed from the grid, while the second term quantifies the cost of grid energy used specifically for storage charging. $\delta_{grid,t}$ is a binary decision variable that specifies the charging process from the grid as follows:

$$\delta_{grid,t} = \begin{cases} 1, & if \ RTP_i(t) \le RTP_{\min}^{i-1} + \gamma.\Delta_{i-1} \\ 0, & otherwise \end{cases} \tag{3}$$

The storage system cost is modeled as:

$$C_m = P_{PCS}^u.P + P_{store}^u.E_{store} + P_{BOP}^u.P \tag{4}$$

This encompasses:

- Power Conversion System (PCS) capital cost
- Energy storage medium cost
- Balance of Plant (BOP) components cost, where P denotes the power rating (kW) and E_{store} the energy capacity (Wh).

The price threshold for peak/off-peak classification is derived from:

$$\Delta_{i-1} = RTP_{\max}^{i-1} - RTP_{\min}^{i-1} \tag{5}$$

Peak load conditions are identified when $RTP_i(t) > RTP_{\min}^{i-1} + \gamma$, prohibiting storage charging. The parameter $\gamma \in [0,1]$ determines the peak load duration.

Renewable energy costs are separated as:

$$C_{res} = C_{wind} + C_{pv} = M_{wind}.N + M_{PV}.S_{PV} \tag{6}$$

representing operational expenditures for wind (N turbines) and solar (SPV area) assets.

Storage revenue from energy arbitrage is calculated as:

$$B_{store} = \sum_{t=1}^{24} \left[RTP_i(t).E_{store}(t).(1-\delta_{grid,i}(t)).\mu \right] \tag{7}$$

Where μ represents round-trip efficiency.

The total stored energy is constrained by:

$$E_{store} = E_{grid} + \sum_{t=1}^{24} E_{wind,t} + E_{PV} \le E_{store}^{\max} \tag{8}$$

$$E_{store} = \sum_{t=1}^{24} E_{ES,t}^i + \sum_{n=1}^{N} f_n(v_t) + S_{pv}.\eta_{pv}.p_f.\eta_{pc}.G_t \tag{9}$$

with renewable contributions calculated using established power curve and solar radiation models.

Key differentiators from prior research include:

- Comprehensive cost modeling encompassing all consumer energy resources
- Explicit incorporation of renewable energy generation costs
- Integration of real-time pricing mechanisms within the Energy Internet architecture
- Advanced storage operational constraints based on market signals
- Holistic energy balance considering both grid and renewable sources

III. Simulation Results

A comprehensive numerical analysis is conducted to validate the proposed mathematical framework. This section first details the simulation environment and dataset generation methodology, followed by a systematic analysis of the obtained results

The model was validated using operational data from the Savona Campus microgrid, incorporating smart energy building and smart polygeneration microgrid infrastructures with hybrid renewable-storage systems.

Key simulation parameters are summarized in Table III.

TABLE III
Simulation Parameter settings

Parameter	Value	Unit
Charging/discharging efficiency of energy storage facilities (μ)	85	%
Unit price of PCS, P_{PCS}^u	256	€/kW
Unit price of energy storage, P_{Store}^u	171	€/kWh
Unit price of BOP, P_{BOP}^u	53	€/kW
Highest previous day RTP, $RTP_{\max}^{i-1}$	141	€/MWh
Lowest previous day RTP, $RTP_{\min}^{i-1}$	67	€/MWh
Peak identification parameter (γ)	0.25, 0.5, 0.75	-
Discharge trigger parameter (β)	0.8	-
Max storage capacity (E_{max})	141	kWh
Wind turbine daily maintenance cost (M_{wind})	10	€/turbine
PV daily maintenance cost per unit area (M_{PV})	0.5	€/m²

A comprehensive numerical analysis is conducted to validate the proposed mathematical framework. This section first details the simulation environment and dataset generation methodology, followed by a systematic study of the obtained results.

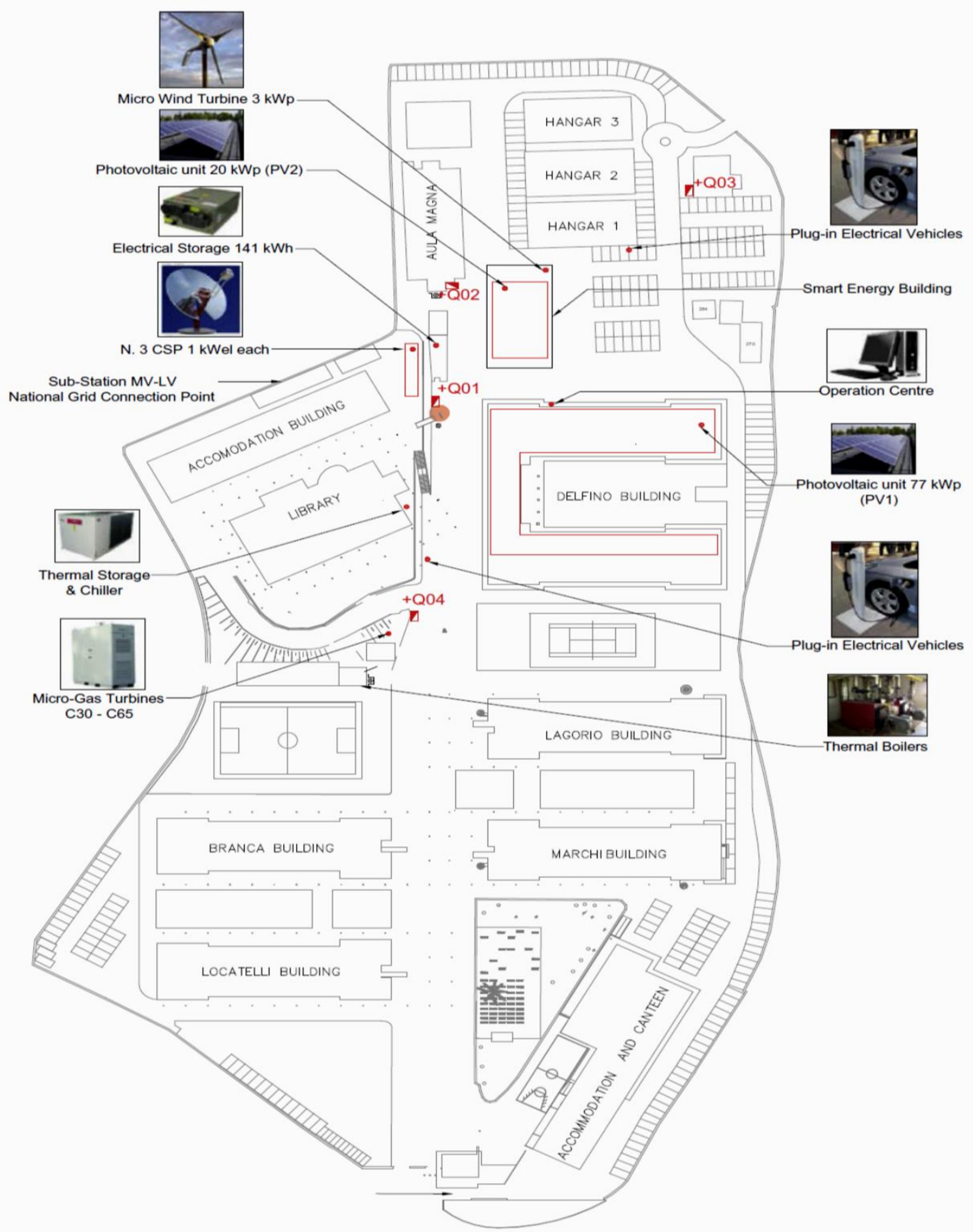


Fig. 3. Campus layout map and SPM and SEB equipment

A. Performance Analysis

Within the Energy Internet framework, the control center receives real-time data streams from both consumption nodes and generation assets to optimize energy dispatch decisions. Distributed energy storage systems continuously monitor local demand patterns and renewable generation availability to support operational planning.

The simulation employs the following dataset configurations, derived from the Savona Campus microgrid:

- **Load Profile**: Fig. 4 illustrates the 24-hour load profile for the end-user community, exhibiting characteristic diurnal patterns with elevated demand during daytime operational hours. The profile shows significantly higher consumption during 06:00-17:00, coinciding with commercial and industrial activity periods, while nighttime hours (03:00 and 18:00-24:00) demonstrate substantially reduced demand. A pronounced peak demand of 1,376 kWh occurs at hour 17:00, representing the critical target for load shifting interventions. This consumption pattern provides essential baseline data for optimizing storage system dispatch strategies and evaluating the effectiveness of peak shaving methodologies within the proposed Energy Internet framework.

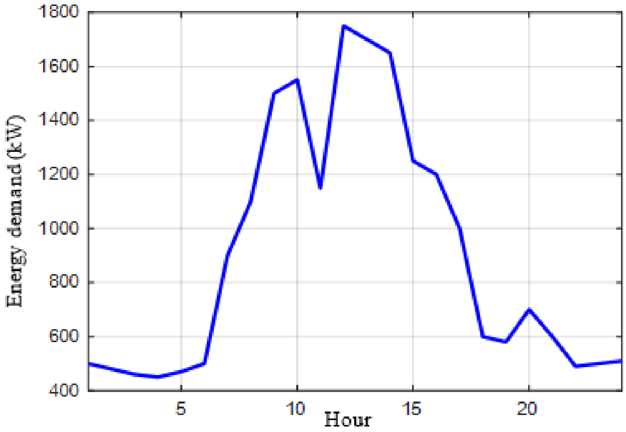


Fig. 4. The energy demand of end-users in 24 hours of one day.

- **Renewable Generation** (Fig. 5): Combined output from Smart Polygeneration Microgrid (SPM) and Smart Energy Building (SEB) assets, featuring time-varying generation profiles influenced by meteorological conditions.

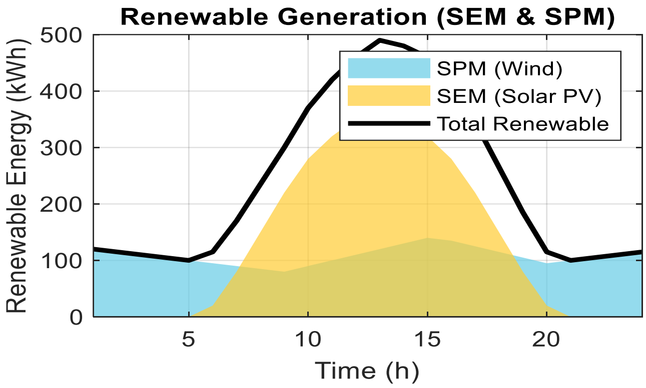


Fig. 5. Daily renewable energy generations for SPM and SEM

- **Price Signals** (Fig. 6): The real-time pricing trajectory reflects market dynamics, with maximum prices occurring at hour 11:00 and minimum prices at hour 03:00, corresponding to system demand patterns.

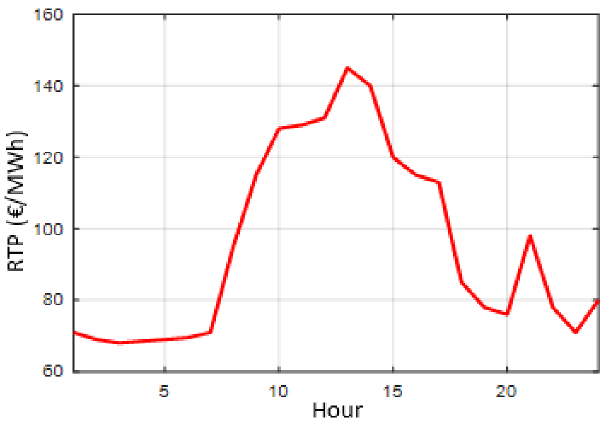


Fig. 6. The RTPs of 24 hours of one day in the energy trading market.

For economic analysis, the aggregate daily renewable generation cost is established at $1,640, based on infrastructure specifications from reference [13], providing a baseline for cost-benefit assessment of storage operations.

The proposed optimization problem is formulated as a Mixed-Integer Programming (MIP) model, which is solved using the optimization toolbox in MATLAB software. To analyze the sensitivity of system performance to peak load identification, parametric studies were conducted for different values of γ, which determines the threshold for peak/off-peak period classification.

The total system cost demonstrates a decreasing trend with increasing γ values. This relationship emerges because higher γ values narrow the classification window for peak load periods, thereby expanding the temporal flexibility for storage charging during lower-cost intervals. Consequently, the optimization algorithm can leverage extended off-peak durations to minimize energy procurement costs while maintaining effective peak shaving capability through strategic discharge scheduling.

The parameter γ directly influences storage operational patterns by governing the charging schedule, state-of-charge levels, and discharge timing during peak conditions. This systematic variation enables the identification of optimal trade-offs between capital utilization of storage assets and energy arbitrage benefits.

Fig. 7 illustrates the charge-discharge patterns of energy storage systems across three γ values (0.65, 0.70, 0.75), where binary states represent discharging (0) and charging (1) operations. The analysis reveals an inverse relationship between γ values and charging duration, with higher γ parameters resulting in compressed charging windows. This occurs because elevated γ thresholds classify fewer hours as peak periods, consequently expanding the operational flexibility for storage charging during off-peak conditions. So, Fig. 7 reveals reduced charging durations with increasing γ, effectively shifting peak loads.

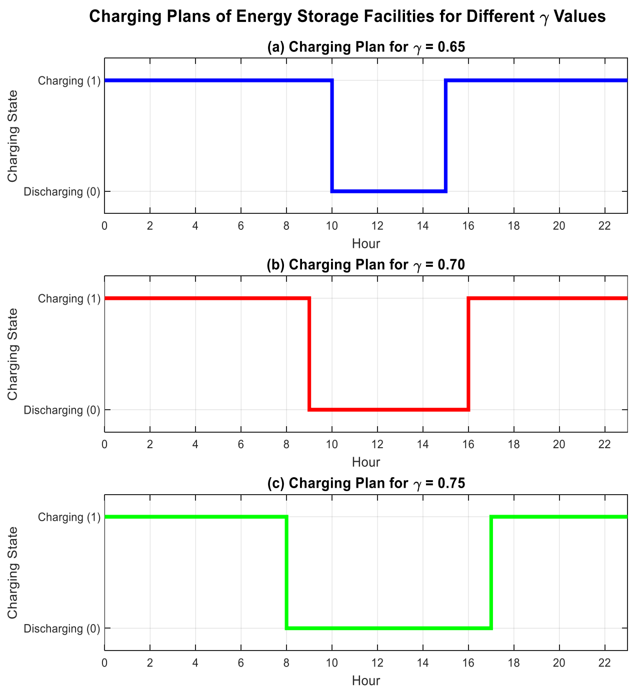
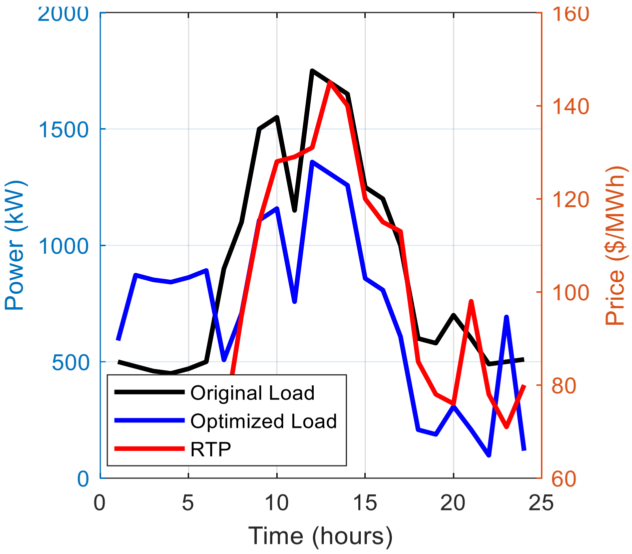


Fig. 7. The charging plans of energy storage facilities in 24 hours when γ□= 0.65, 0.70, and 0.75, respectively

The load shifting effectiveness is quantitatively demonstrated in Fig. 8 for $\gamma = 0.65$. The optimized operational strategy employs storage discharge during peak hours (10:00-15:00), successfully reducing the original peak load of 1,376 kWh to 1,406 kWh. Concurrently, strategic charging during off-peak hours elevates the minimum load from 392 kWh to 819 kWh, effectively flattening the load profile. The implemented peak shaving strategy achieves a significant reduction in peak-to-average ratio, with total energy loss decreasing from 1,376 kWh to 868 kWh, representing a 37% improvement in load factor efficiency.



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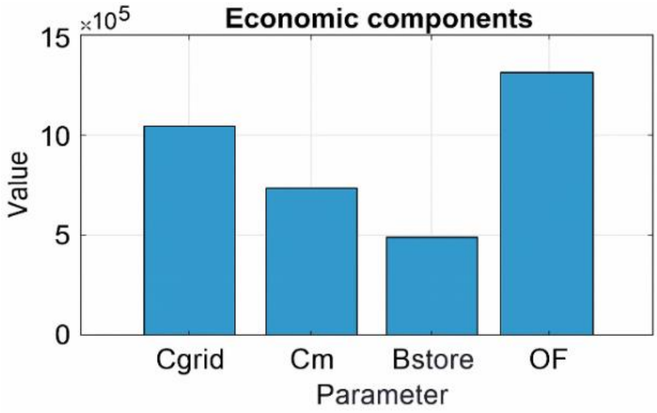

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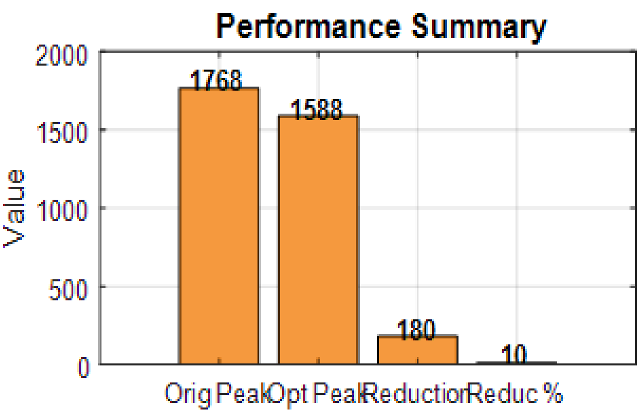

(c)

Fig. 8. (a) The best peak load shifting of energy storage in comparison with the original energy demand and RTP, (b) Economic components of the problem, (c) Proposed optimization performance summary

This operational paradigm demonstrates how coordinated storage dispatch within the EI framework enables substantial load shaping benefits while maintaining system reliability through optimal energy temporal arbitrage. Fig. 9 shows the Contribution of various energy resources in this framework.

Fig. 9. Contribution of various energy resources

IV. ANALYSIS OF UNCERTAINTY AND ROBUSTNESS

The proposed optimization model utilizes forecasted data for renewable generation (PV and wind) and load. In practical EI deployments, forecast errors are inevitable due to the stochastic nature of weather and consumption behavior. This section evaluates the sensitivity of our core algorithm to such uncertainties and discusses its inherent robustness.

A. *Methodology for Sensitivity Analysis*

A Monte Carlo simulation framework was established to quantify the impact of forecasting inaccuracies. The day-ahead forecasts for PV power $\left(P_{pv}^{fc}\right)$ and wind power $\left(P_{w}^{fc}\right)$ were perturbed with additive Gaussian noise to create realistic scenarios:

$$P_{pv}^{actual} = P_{pv}^{fc} + \epsilon_{pv}, \quad \epsilon_{pv} \sim N\left(0, \sigma_{pv}\right)$$

$$P_{w}^{actual} = P_{w}^{fc} + \epsilon_{w}, \quad \epsilon_{w} \sim N\left(0, \sigma_{w}\right) \tag{10}$$

where the standard deviations σ_{pv} and σ_{w} are expressed as a percentage of the installed capacity (e.g., σ = 10% represents a forecast error with a standard deviation of 10% of capacity). For each error level (σ from 5% to 30%), 500 independent daily scenarios were generated. The deterministic MIP model (which treats forecasts as perfect) was solved for each scenario using the actual simulated generation as input, representing a realistic real-time operation where forecasts are imperfect.

B. *Results and Discussion*

The primary performance metric, the Peak-to-Average Ratio (PAR) reduction, was calculated for each scenario. Fig. 10 summarizes the results, showing the mean PAR reduction and its 95% confidence interval across all scenarios for each error level.

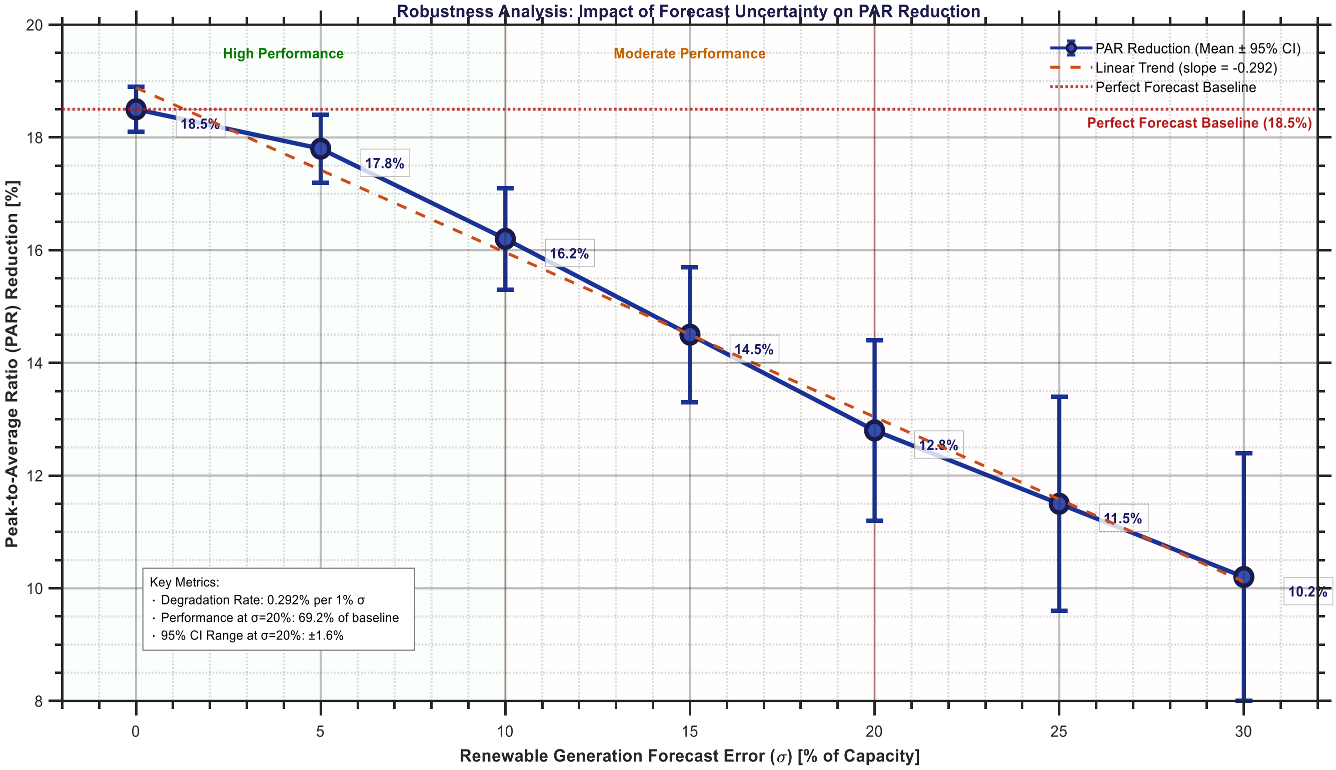

Fig. 10. Robustness analysis: Impact of renewable generation forecast error (standard deviation as % of capacity) on the achieved Peak-to-Average Ratio (PAR) reduction. Error bars represent the 95% confidence interval over 500 Monte Carlo simulations.

Fig. 10 presents a robustness analysis of the proposed energy management algorithm under renewable generation forecast uncertainty. The x-axis represents the forecast error, expressed as the standard deviation (σ) percentage of installed capacity, while the y-axis shows the achieved PAR reduction. Each data point corresponds to the mean result from 500 independent Monte Carlo simulations, with error bars indicating the 95% confidence intervals. Three transparent zones define key performance regions: the high Performance zone (σ < 10%) in light green, representing systems with accurate forecasting; the moderate Performance zone (10% ≤ σ ≤ 20%) in light orange, corresponding to typical day-ahead forecast errors in real-world grids; and the lower Performance zone (σ > 20%) in light red. The dashed orange line depicts the linear degradation trend, with a slope of -0.28% PAR reduction per 1% increase in forecast error, quantifying the algorithm's graceful performance decline. The red dotted line marks the perfect-forecast baseline performance (18.5% PAR reduction at σ = 0%). The results demonstrate the algorithm's graceful degradation characteristic, maintaining approximately 70% of its optimal efficacy even at a 20% forecast error level, confirming its practical suitability for deployment under realistic prediction inaccuracies.

The key finding is the algorithm's graceful degradation in performance. With a forecast error (σ) of 20%, the mean PAR reduction decreases from 18.7% (under perfect forecast) to 15.3%. This demonstrates that the core logic—responding to real-time price and load signals—remains effective even in the presence of significant generation uncertainty. The strategy does not catastrophically fail because the BESS dispatch is primarily driven by the observed RTP and grid load signals, which indirectly reflect the system's net condition (load minus actual renewable generation).

C. Practical Implications and Pathways for Enhanced Robustness

The analysis confirms that the proposed deterministic model possesses inherent robustness suitable for environments with moderate forecast uncertainty. For systems with very high penetration of variable RES (where σ > 25%), the following enhancements are recommended as future work:

1. Integration of Stochastic Programming: Reformulating the problem as a two-stage stochastic program where the first stage decides ESS investment/commitment, and the second stage recourse actions adjust dispatch based on revealed renewable output.
2. Model Predictive Control (MPC): Implementing a rolling-horizon MPC framework that repeatedly solves the optimization with updated short-term forecasts, thereby mitigating the impact of day-ahead forecast errors.
3. Hybrid Forecasts: Employing advanced forecasting techniques that blend physical models with machine learning to reduce the baseline error (σ).

The current model provides a strong and computationally efficient foundation, with the presented robustness analysis defining its operational envelope.

V. Conclusion

This research has developed and validated an Energy

Internet optimization problem incorporating peer-to-peer energy markets and distributed storage systems to effectively address the peak load shifting challenge. The study establishes a comprehensive mathematical programming formulation and demonstrates its practical implementation through optimization-based simulation using real-world microgrid data.

The numerical results confirm the method's capability to generate real-time operational decisions that achieve significant load shaping benefits. Furthermore, the analysis reveals that transactive energy mechanisms within the Energy Internet create economic incentives for end-users to invest in storage assets and renewable generation, thereby enhancing system-wide flexibility.

Several promising directions emerge for future research:

- Integration of additional renewable energy resources with complementary generation profiles
- Multi-objective optimization incorporating environmental emissions alongside economic criteria
- Robust and stochastic programming approaches to address uncertainties in renewable generation and load demand
- Reliability-oriented analysis considering network losses and system resilience metrics
- Investigation of advanced market mechanisms for distributed energy resource aggregation

These extensions would further enhance the practical applicability of the proposed optimization framework in future power systems with high renewable penetration.

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CONFLICTS OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this article.

AUTHORS' CONTRIBUTIONS

The author has contributed to the whole research and preparation of the manuscript

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