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Deep Learning Based Optimal Energy Management in the Presence of Renewable Energy

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Abstract— *Traditional energy management focuses on ensuring a reliable and sustainable energy supply through meticulous planning, coordination, and optimization of resources. However, integrating renewable energy sources like solar, wind, and hydropower introduces a new layer of complexity. These sources, while environmentally friendly, are inherently intermittent and variable in their production, posing unique challenges for energy management. Effective energy management in the presence of renewable energy requires strategies to balance supply and demand, optimize energy use, and ensure grid stability. This study introduces a new model designed to significantly improve the accuracy of estimating both energy production and demand. This enhanced level of precision plays a decisive role in the decision-making process for energy management. This innovative model employs a fuzzy neural network trained on historical energy production data, integrating weather information through fuzzy functions to improve precision in estimating energy production for future intervals. The objective functions prioritize renewable energy use to minimize overall system costs. The simulations evaluated the total system cost under various conditions. The results showed that more accurate estimation and maximized utilization of renewable energy sources led to a significant reduction in the cost per kilowatt-hour. In essence, this study offers a promising approach to managing energy systems that heavily rely on renewable sources. By improving estimation accuracy and prioritizing renewable energy use, the model paves the way for a more reliable, sustainable, and cost-effective energy future.*

Keywords—Energy management, renewable energy, lSTM-fuzzy network, power production forecast.

1. Introduction

The increasing penetration of renewable energy sources, such as solar and wind power, has significantly impacted the dynamics of energy management in modern power systems [1]. With the intermittent and uncertain nature of renewable energy generation, the optimal energy management becomes a complex and challenging task. Deep learning, a subset of artificial intelligence, has shown promising potential in addressing these challenges by enabling more accurate predictions and real-time decision-making [2]. In this context, the application of deep learning-based techniques for optimal energy management has gained considerable attention in recent years. This paper aims to explore the role of deep learning in optimizing energy management in the presence of renewable energy, considering its ability to handle large-scale, complex, and non-linear data sets. By leveraging deep learning algorithms, it is possible to develop more robust and adaptive energy management systems that can effectively integrate renewable energy sources, enhance grid stability, and minimize operational costs. This paper will delve into the key concepts and methodologies of deep learning-based optimal energy management, highlighting its potential to revolutionize the way renewable energy is integrated and utilized within power systems [3]. The electric grid must modify the generation units, which is one of the key components involved in integrating renewable energy sources into the main system. By integrating renewable energy sources into the main grid, many technical and financial issues might arise (Fig. 1). Therefore, in order to optimize the use of renewable energy in the network, it is necessary to implement energy monitoring and management methods.

The growing adoption of renewable energies, driven by their capacity to reduce greenhouse gas emissions, has led to the emergence of various approaches aimed at optimizing and effectively managing energy within these systems. In [4] a combination of batteries, electric vehicles (EVs), and other energy sources is used to capture the fluctuations of renewable energy sources (RESs). Then, to effectively represent the uncertainties associated with RESs, energy prices, and load demands, a linearized stochastic programming framework is utilized. [5] introduces a novel energy management system model for a residential microgrid that incorporates a battery energy storage system (BESS). The proposed dynamic model combines a predictive model based on deep learning, specifically bidirectional long short-term memory (Bi-LSTM), with an optimization algorithm. [6] introduces a pragmatic framework for achieving optimal energy management and control in renewable microgrids (MGs) by incorporating energy storage devices, wind turbines, and microturbines. To efficiently solve the power flow dispatch in the system, the teacher learning-based optimization (TLBO) technique is employed. Additionally, a novel hybrid deep learning model, which integrates principal component analysis (PCA), convolutional neural networks (CNN), and bidirectional long short-term memory (BLSTM), is proposed

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to address the challenge of short-term wind power forecasting. [7] investigates the impact of different weather conditions on the power generation of the PV unit and explores the optimal scheduling strategy for the MG. So, solar irradiance data from four representative days in each of the four seasons are collected and analyzed. The scheduling problem is formulated as a single-objective optimization framework, where the objective function aims to minimize the total operating cost over the scheduling period. [8] focuses on the integration of a community energy storage system (CESS) with a photovoltaic (PV) system. The research aims to determine the scheduling decisions for both the CESS and utility grid by establishing appropriate constraints. In order to analyze the operational behavior of microgrids (MGs) and minimize network energy losses, a scenario-based energy management system (EMS) that is modelled as a mixed-integer linear programming (MILP) problem is presented [9]. To maximize the energy-saving potential of thermostatically controllable appliances (TCAs) while meeting operational and comfort constraints, a demand response (DR) program based on direct load control (DLC) is introduced into the system. In [10] a PV energy storage system (CESS) is considered where the scheduling decision of the CESS and utility grid can be subsequently achieved through LSTM. [11] proposes a novel robust framework for the day-ahead energy scheduling of a residential microgrid comprising interconnected smart users, each owning individual RESs, noncontrollable loads (NCLs), energy- and comfort-based CLs, and individual plug-in electric vehicles (PEVs). [12] proposes a joint and conceptual approach for the techno-economic design and dynamic rule-based power control of an off-grid hybrid renewable energy system that combines solar and wind power, along with a hybrid energy storage system that consists of a supercapacitor, a lead-acid battery, and a lithium-ion battery. In the grid-connected microgrid systems, [13] provides a two-stage multi-objective framework that concurrently lowers operating costs and improves demand response program efficiency. In order to assess the energy flexibility of the demand response systems, it also presents the Average Power Flexibility during Peak Period Index (APFDPPI). In the presence of renewable energy sources, [14] discussed the modeling and optimization of electric car charging using genetic algorithms. [15] developed a model that accurately replicates a microgrid, predicts demand and supply, seamlessly schedules power delivery to meet demand, and gives actionable insights into the SG system's operation. In [16] a new approach is presented to designing hybrid energy systems using the Firefly algorithm. It aims to enhance resilience and adaptability while reducing environmental impacts by incorporating multiple energy sources like solar panels, wind turbines, and combined heat and power systems. By considering uncertainties in production capacity, demand, and costs, the study demonstrates the algorithm's effectiveness in optimizing system design compared to other methods. [17] explores energy management strategies for microgrids and smart electrical grids, with a focus on leveraging electric vehicles (EVs) as potential energy sources. By considering market prices of energy, prices from distributed generation sources, and EVs in the grid, along with responsive loads, the study investigates load response programs such as time of use and direct load control. Using linear mixed-integer planning simulated with GAMS software, the research demonstrates that implementing these load response programs can effectively reduce costs. A mathematical model for grid-connected microgrids, incorporating various generation sources and an improved demand response program is presented [18]. The novelty lies in a new uncertainty modeling technique based on copula functions and scenario generation. Using the group search optimization (GSO) algorithm, the paper optimizes operational cost and environmental pollution.

Many of the examined studies have focused on the fluctuation of renewable energies and have proposed models for predicting and managing their energy output. Nevertheless, there is a need to develop more precise estimation methods. Additionally, it is crucial to incorporate the variability in consumer demand into decision-making criteria. Consequently, this article introduces the following:

1) Enhancement of the accuracy in estimating renewable energy production.
2) Introduction of a neural-fuzzy network model for assimilating new data.
3) Integration of demand quantity into energy management considerations.

The remaining sections of the article are structured as follows: Section 2 addresses problem modeling, introducing renewable energy sources and methods for enhancing their production estimation. Section 3 presents the system's energy management approach. Section 4, simulation and numerical results are showcased, and ultimately, Section 5 provides the summary and conclusions.

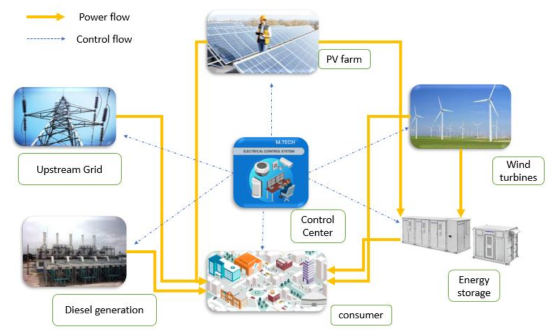

Fig. 1. The model of using renewable energy in the grid.

2. System model

The model shown in Fig. 1 is intended to implement methods to optimize energy consumption. A series of renewable energy producers along with the power grid and diesel power plant deliver electrical energy to consumers. Energy storage resources have also been used to manage network energy. In the following, the model of renewable producer sectors is presented along with the energy optimizer model.

2.1. Wind turbine

One of the best renewable energy sources for making electricity is wind energy. Thanks to new power system innovations and faster turbine technologies, the wind sector is growing quickly. Synchronous or induction motors are used in wind generators. Owing to their compact size, low weight, and ease of maintenance, induction motors are extensively utilized. The mathematical model of wind turbines is presented below [19].

The total power:

$$P_w = \frac{1}{2}\rho A_s v_w^3 \tag{1}$$

The total available wind power:

$$P_T = \frac{1}{2}\rho C_p \zeta A v_w^3 \tag{2}$$

Where, P_w= Power (W), m= Mass (Kg), v_w= Speed of wind (m/s), ρ= Density (Kg/m^3), A_s= Swept area (m^2), and ζ= Speed ratio.

2.2. PV farm

There are two ways that the PV energy can be converted. The direct use of photovoltaic phenomena to generate power is known as photovoltaic. The photovoltaic system experiences fluctuations in DC current as a result of variations in solar intensity. By employing an inverter to supply the proper voltage and current, this volatility is lessened. A concentrated solar power system is an indirect technique that generates electricity by using mirrors or lenses. The following equation show the governing equations of photovoltaic cells based on equivalent circuit model of PV unit shown in Fig. 2 [16].

$$I = (N_{cp}I_{pc} - N_{cp}I_{mc}) \times [\exp(\frac{V/N_{cs}+IR_s/N_{cp}}{NV_{dt}}) - 1] - I_{rc} \quad (3)$$

$$V_{dt} + \frac{KT}{Q} \quad (4)$$

$$I_{rc} = \frac{VN_{cp}/N_{cs} + IR_s}{R_{sr}} \quad (5)$$

I_{pc}= Photo current (A); N_{cp}= Cell number connected in parallel; I_{mc}= Module saturation current; N_{cs}= Cell number connected in series; Q= Charge of electron; K= Boltzmann's constant: T = Actual cell temperature;

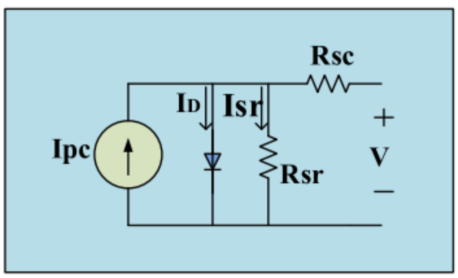

Fig. 2. Equivalent circuit model of PV unit.

3. Optimizing energy in the network

Even though using renewable energy has numerous advantages, the grid faces difficulties because of its unpredictable nature. In order to overcome this challenge, in the proposed method, energy storage devices along with algorithms have been presented to accurately predict production schedules and demand.

3.1. Wind/PV generation prediction

Wind energy can be used on a large scale to generate electrical power. In order to estimate the amount, various methods have been presented in past research. However, in order to estimate it more accurately, it is necessary to consider information such as weather information. In this regard, in the proposed method, weather information is combined with power generation information by a fuzzy network to provide a more accurate estimate.

As illustrated in the Fig. 3, the weather data is converted into vectors through a set of fuzzy functions, positioned alongside power generation information, and subsequently input into the LSTM network.

A more advanced version of the RNN, referred to as an LSTM network, overcomes its limitations by integrating memory cells and multiple control gates. These memory cells allow LSTM networks to capture long-term dependencies in temporal sequences, facilitating the flow of information across consecutive time steps within the internal network structure. Fig. 4 illustrates

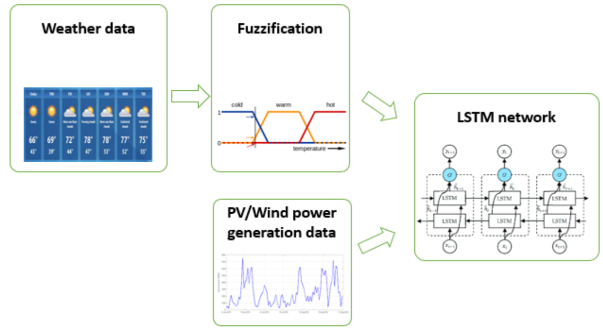

Fig. 3. Proposed structure for wind power generation.

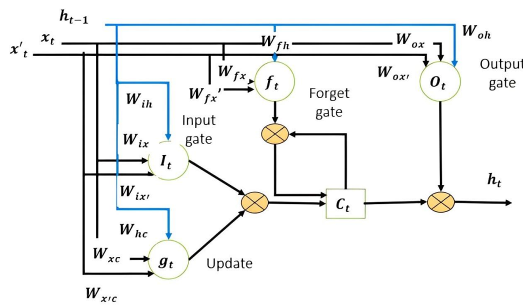

Fig. 4. Single-cell structure of an LSTM.

the single-cell structure of an LSTM, featuring three gates (input gate, output gate, and forget gate).

However, an LSTM layer consists of interconnected single cells. Let X_t represent the wind-generated power or energy measurement at time step t. The relationship between the current and previously observed data is formulated as follows to predict the 24-hour-ahead response of the wind-generated power or energy consumption.

$$\left(\hat{Y}_{t+1}, \hat{Y}_{t+2}, \ldots, \hat{Y}_{t+24}\right) = LSTM\left(X_{t-k+1}, \ldots, X_{t-1}, X_t\right) \quad (6)$$

Here, t belongs to the interval $[k,\ N-1]$, where k is the time lag, and N is the size of the data. In the equation, LSTM($\cdot$) denotes the LSTM function for each individual cell L within the range of 1 to NL, and is defined by the following:

$$\begin{aligned} i_t &= \sigma\left(\vec{W}_i\left[\vec{h}_{t-1}, x_t\right] + b_i\right) \\ f_t &= \sigma\left(\vec{W}_f\left[\vec{h}_{t-1}, x_t\right] + b_f\right) \\ C_t &= f_t \cdot C_{t-1} + (1 - f_t) \cdot \tanh\left(\vec{W}_c\left[\vec{h}_{t-1}, x_t\right] + b_C\right) \\ o_t &= \sigma\left(\vec{W}_o\left[C_t, \vec{h}_{t-1}, x_t\right] + b_o\right) \\ \vec{h}_t &= o_t \cdot \tanh\left(C_t\right) \end{aligned} \quad (7)$$

The same structure is used for PV-gerated prediction.

3.2. Energy consumption management

Once the precision of estimating renewable resource generation is enhanced, attention must be directed towards devising policies for governing energy consumption within the grid. Every component of the grid, such as renewable sources, energy storage units, diesel power plants, and others, contributes costs to the grid that necessitate careful consideration. To address this, the comprehensive cost function of the network is conceived as the aggregate of the cost functions associated with various segments of the network, as outlined below:

$$\begin{array}{l} \max \quad P_{wind} + P_{Pv} \\ \min \quad P_{disel} \ + P_{network} \\ CS: StorageCapacity < \gamma_s, Totall\_power > \gamma_{th} \end{array} \tag{8}$$

$$\begin{array}{l} \text{Cost}_{kW} = 400 \times \text{Cost}_{PV} + 190 \times \text{Cost}_{wind} + 250 \times \\ \text{Cost}_{storage} + 350 \times \text{Cost}_{Diesel} + 300 \times \text{Cost}_{Network} \end{array} \tag{9}$$

Where 400, 190, and 350 are generated power in KW by PV, wind, and diesel powerplants respecticely. Also, 250 (KW) is the cpacity and 300 (KW) is the network power consumption.

4. Numerical results

In order to evaluate the presented model, it is necessary to analyze its numerical results using simulations. Therefore, the model shown in Fig. 5 is implemented in Simulink environment. Since neural networks require a large amount of data for training, this implemented model has been used to create data. 1,000 four-hour samples have been produced and stored for each of the wind energy, solar energy and consumer demand sectors. Then the fuzzy neural network model shown in the figure is used to estimate the wind and solar energy sectors.

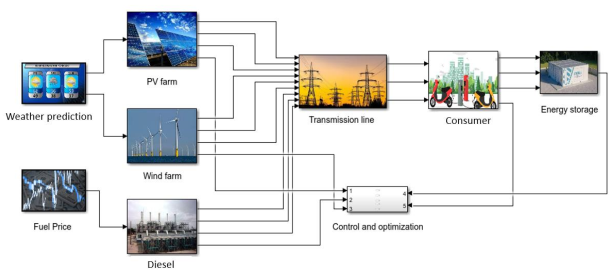

Fig. 5. Simulated model in SIMULINK.

In order to produce the energy of each of the renewable energy units, random variables are placed in specific intervals at the input of their resources to model their stochastic behavior. Then the energy produced from them is stored and used for training. Figs. 5 and 6 show the actual and estimated amounts for wind and solar energy, respectively. These values are for the test data and it shows that the designed network can estimate the production values well. These estimated values can be used in energy management process. The influence of environmental factors, such as wind dynamics, on the accuracy of renewable energy predictions is vividly illustrated in Fig. 6. This figure showcases the considerable variability in wind patterns, which directly impacts the precision of forecasting models. The fluctuations in wind speed and direction contribute to higher error rates compared to the more consistent and predictable nature of photovoltaic (PV) generated power, as depicted in Fig. 7.

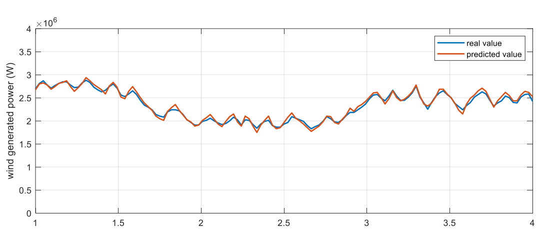

Fig. 6. Actual and estimated amount of produced wind energy.

Understanding and accounting for this variability is paramount when designing forecasting methodologies within renewable energy systems. These findings highlight the critical importance of developing robust models that can adapt to dynamic environmental conditions. Incorporating advanced data analytics and machine learning algorithms can enhance the accuracy of predictions, enabling more effective energy management strategies. Moreover, these insights underscore the necessity of holistic approaches to energy planning, especially in contexts where wind power plays a significant role in the energy mix. By considering the inherent variability of renewable energy sources, decision-makers can better anticipate fluctuations in energy generation and optimize resource allocation accordingly. This proactive approach not only improves the reliability of energy supply but also minimizes costs and enhances overall system efficiency.

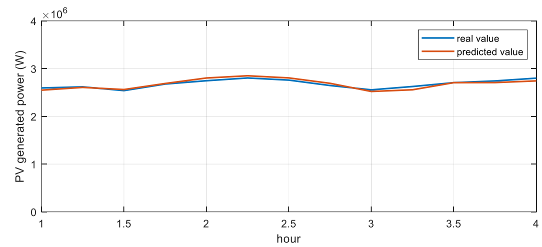

Fig. 7. Actual and estimated amount of produced PV energy.

In addition to environmental factors, accurately estimating consumer demand is another essential parameter in effective energy management. By leveraging available data on demand patterns, organizations can optimize the utilization of resources, including renewable energy production and energy storage. This optimization leads to more efficient allocation of resources, reduces reliance on traditional energy sources, and ultimately lowers operational costs. Overall, by acknowledging and addressing the complexities of renewable energy forecasting and demand estimation, stakeholders can pave the way for a more sustainable and resilient energy future. This requires a multidisciplinary approach, integrating technological advancements, data-driven insights, and strategic planning to maximize the benefits of renewable energy sources while minimizing their inherent challenges.

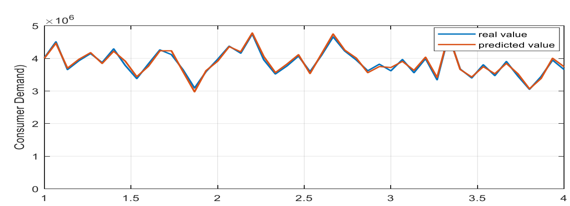

Fig. 8. Actual and estimated amount of Consumer demand.

Ultimately, once the desired values are estimated, it becomes feasible to ascertain the values for each production and storage unit using Eq. (1). Subsequently, the cost is determined based on this equation. In Fig. 9, the cost for the system under consideration are presented, depicting results for two modes: Utilizing the estimation model and making decisions based on measured values. The results indicate that when production quantities for each unit are accessible, the cost per kilowatt of production power decreases by approximately \$220, signifying a noteworthy reduction on a larger scale.

The numerical result (Fig. 10) reveals that the enhanced model, incorporating weather information and LSTM networks, outperforms the traditional model in terms of prediction accuracy and robustness. Specifically, the enhanced model exhibits lower mean squared error (MSE) (given by Eq. (10)) values across various test datasets compared to the model in [19].

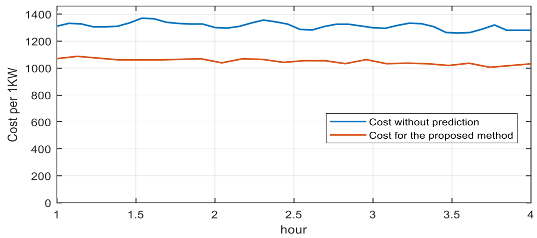

Fig. 9. The cost value of proposed method.

$$MSE = \frac{1}{n}\sum_{1}^{n}\left(\frac{A_t - F_t}{A_t}\right)^2 \tag{10}$$

The figure demonstrates that the proposed method consistently outperforms the method referenced in [19] in terms of MSE. This suggests that the proposed method provides more accurate predictions or estimations throughout the observed period. The lower MSE values indicate a significant improvement, which is crucial for applications requiring precise energy management, prediction, and optimization. In conclusion, the proposed method's superior performance, as evidenced by consistently lower MSE values, validates its effectiveness and potential for enhancing reliability and accuracy in the relevant applications. This improvement is particularly notable under conditions of varying weather patterns and environmental factors, where the traditional model may struggle to capture the complexities of renewable energy generation.

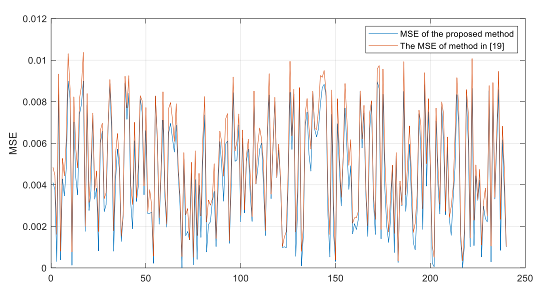

Fig. 10. Wind and solar power generation MSE: Proposed vs. Method in [19].

Also, the Mean Absolute Percentage Error ($MAPE$) which is a widely used metric for assessing the accuracy of forecasting methods is calculated for both methods. It provides a clear indication of how accurate forecasts are by expressing the average absolute percentage difference between the predicted and actual values. The formula for calculating $MAPE$ is as follows:

$$MAPE = \frac{1}{n}\sum_{1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \tag{11}$$

Where, n is the number of observations, A_t is the actual value at time t, and F_t is the forecasted value at time t. The $MAPE$ value for the proposed method and the method in [20] is 11% and 16%, respectively. The model in [20] presents a methodology for energy forecasting utilizing Renewable Energy Sources (RESs), emphasizing the deployment of Deep Neural Network (DNN) models on mobile devices located at the network edge. However, due to its omission of weather information and complete historical data, it exhibits reduced accuracy in predicting renewable energy generation.

5. CONCLUSION

This study introduces an innovative energy management approach tailored for power networks integrating variable renewable energy sources. Leveraging neural-fuzzy networks, the model achieves remarkable precision in estimating production for renewable units, as evidenced by a significantly lower Mean Absolute Percentage Error ($MAPE$) value of 11% compared to 16% for the previous methods in the literature. This improvement in accuracy translates into tangible benefits, as demonstrated by a reduction in the cost per kilowatt-hour of production power by approximately \$220, as highlighted in the results. This refined estimation capability proves instrumental in optimizing energy management strategies, enabling the model to consider unit costs and storage dynamics to determine the most efficient production quantities for each renewable source. Consequently, the model significantly boosts renewable energy production while simultaneously curbing overall system costs. This achievement underscores the efficacy of neural-fuzzy networks in addressing the inherent unpredictability of renewable energy production, thereby enhancing the network's stability and efficiency. Moreover, the model's integration of unit costs and storage options ensures a financially prudent approach to energy management, further corroborated by the tangible cost reductions observed in the study. Future endeavors may explore integrating additional data sources and developing real-time adaptive models to enhance scalability and responsiveness. Additionally, economic analysis, policy integration, and synergy with smart grid technologies are crucial avenues for further exploration and refinement.

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