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Advanced Energy Management System for Renewable Based Microgrids Using Optimization and Intelligent Control Techniques

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ABSTRACT
An advanced Energy Management System (EMS) for renewable-based microgrids is presented using optimization techniques integrated with Artificial Neural Networks (ANN). The proposed system aims to efficiently coordinate distributed energy resources such as photovoltaic (PV) systems, wind turbines, battery energy storage systems (BESS), and grid interaction to ensure reliable and economical operation. ANN is employed for accurate load and generation forecasting, while optimization algorithms are used to minimize operational cost, power losses, and emissions under varying environmental and load conditions. The intelligent control strategy dynamically manages energy flow, maintains power balance, and enhances system stability. Simulation results demonstrate improved efficiency, reduced dependency on the main grid, and enhanced power quality compared to conventional EMS approaches. The proposed methodology offers a scalable and robust solution for modern smart microgrids with high renewable penetration.

Keywords: AI-driven EMS, microgrids, renewable energy integration, load balancing, machine learning

I. INTRODUCTION

Since microgrid (MG) systems can increase sustainability, efficiency, and dependability, they have become vital parts of modern energy distribution networks [1,2]. Renewable energy sources (RESs), energy storage devices, and controlled loads are combined in these distributed energy systems to enable them to operate either independently or in conjunction with the main grid [3,4]. Optimizing MG operation, maintaining stability, and using renewable resources most depend on effective control strategies [5–7]. Because they are straightforward and clear, traditional rule-based control techniques have been extensively employed in MG management systems. Nevertheless, these techniques often have difficulty adjusting to dynamic and uncertain operating conditions, which restricts their use in maximizing system performance [8–10]. To solve these problems and create hybrid control systems for MG management, there is growing interest in merging rule-based control methodologies with deep learning techniques [11]. In order to enable more adaptive and clever control decisions, deep learning models with the ability to comprehend intricate patterns and relationships from historical data include gated recurrent units (GRUs), long short-term memory (LSTM), and recurrent neural networks (RNNs) [12]. Hybrid control approaches can potentially improve machine learning systems' efficiency, stability, and resilience by fusing the interpretability of rule-based systems with the learning power of deep neural networks [13]. In this study, we introduce a novel strategy that combines deep learning technology with rule-based control to optimize MG operation. We thoroughly investigate the hybrid approach's performance against both classic deep learning approaches and independent rule-based control using simulated machine learning circumstances. The findings demonstrate that the proposed strategy enhances MG performance across various environmental factors and load dynamics. This work improves the field of adaptive MG control by introducing a novel framework that combines the advantages of rule-based control and deep learning techniques.

II. POWER SYSTEMS AND AI

Power systems of the modern era are undergoing radical changes which are ever more guided by the imperatives of sustainability, energy independence and resilience with respect to grid disturbance [1]. There is a specific promising direction represented by microgrids, or self-enclosed energy complexes that could exist independently (off the grid), or as a part of the bigger grid. Elasticity in incorporating distributed energy resources (DERs), in particular solar photovoltaics (PV), wind turbines, and battery energy storage systems, makes them ideal in developing smart and sustainable energy solutions [2]. However, efficient management of microgrids is naturally complicated due to changing generation profiles, non-homogeneity of demand, and the very nature of intermittency of any renewable source. The rule based and model predictive controls, designed in the same way, often tend to fail once the stochasticity and non-linearity characteristic of a renewable powered micro grid is presented to them. Artificial Intelligence (AI) is an alternative solution that transforms the situation because it allows adaptive and data-based decision-making [3]. Such methods as machine learning (ML), deep learning, and reinforcement learning have an opportunity to optimize load scheduling practice, improve forecasts and control real-time energy. The following paper introduces an AI-optimized architecture of power management in microgrids. The model combines demand projection, generation prediction and real time decision control in MATLAB-based simulation. The following contributions are significant: A hybrid AI model consisting of a combination of supervised learning and reinforcement learning, a load and generation prediction system that was trained using historical and realtime information, an intelligent control algorithm that aimed to work in a cost- and emission-minimizing manner without violating energy balance. The recommended solution aims at helping energy stakeholders achieve simultaneous goals of the environment and economy by improving the microgrid operations with the help of AI.

III. PROPOSED METHODOLOGY

The proposed work presents an **intelligent Energy Management System (EMS)** for a renewable-based microgrid using an **Artificial Neural Network (ANN)**. The microgrid consists of:

- Solar photovoltaic (PV) system
- Wind energy system
- Battery Energy Storage System (BESS)
- Utility grid (optional)
- Critical and non-critical loads

The EMS is designed to ensure **optimal power sharing, cost reduction, and system stability** under varying environmental and load conditions.

STEP-1 Overall Control Strategy

The proposed methodology is divided into two major stages:

1. **Data-driven ANN training phase (offline)**
2. **Real-time energy management phase (online)**

The ANN replaces conventional rule-based or PI-based controllers by learning optimal decisions from system data.

STEP-2 Data Collection and Preprocessing

A comprehensive dataset is generated in **MATLAB/Simulink** under different operating scenarios, including:

- Variations in solar irradiance
- Wind speed fluctuations
- Load demand changes
- Battery state of charge (SOC) conditions

The collected dataset is:

- Normalized for better ANN performance
- Divided into training, validation, and testing sets

STEP-3 ANN Model Development

Network Structure:

- Type: Feedforward Neural Network
- Layers: Input layer, one/two hidden layers, output layer
- Training algorithm: Levenberg–Marquardt (trainlm)

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Input Parameters:

- Solar power generation
- Wind power generation
- Load demand
- Battery SOC

Output Parameters:

- Optimal power dispatch signals:
  - Battery charging/discharging command
  - Grid power utilization
  - Load management decision

The ANN learns the nonlinear relationship between input conditions and optimal control actions.

STEP-4 ANN Training Process

- The ANN is trained using historical and simulated microgrid data
- Performance is evaluated using:
  - Mean Square Error (MSE)
  - Regression analysis (R-value)

Training continues until:

- Minimum error is achieved
- No overfitting is observed

STEP-5 Real-Time Energy Management

In the online phase:

- Real-time inputs (solar, wind, load, SOC) are fed into the trained ANN
- The ANN instantly generates optimal control decisions
- Power is dynamically allocated among:
  - Renewable sources
  - Battery storage
  - Grid support

This ensures:

- Continuous power supply
- Efficient utilization of renewable energy
- Reduced dependency on grid power

STEP-6 Battery Energy Management Strategy

The ANN intelligently controls battery operation by:

- Charging during excess renewable generation
- Discharging during peak load demand

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- Maintaining SOC within safe operational limits

This improves battery life and system reliability.

STEP-7 MATLAB/Simulink Implementation

The complete system is modeled in **MATLAB/Simulink**, including:

- Renewable energy models
- Load profiles
- ANN controller block (using Neural Network Toolbox)

The ANN is integrated into the Simulink environment for real-time simulation.

Performance Evaluation

The proposed ANN-based EMS is compared with conventional methods (e.g., rule-based or PI controller) based on:

- Energy cost reduction
- Renewable energy utilization
- Battery performance
- Voltage stability
- Response time under dynamic conditions

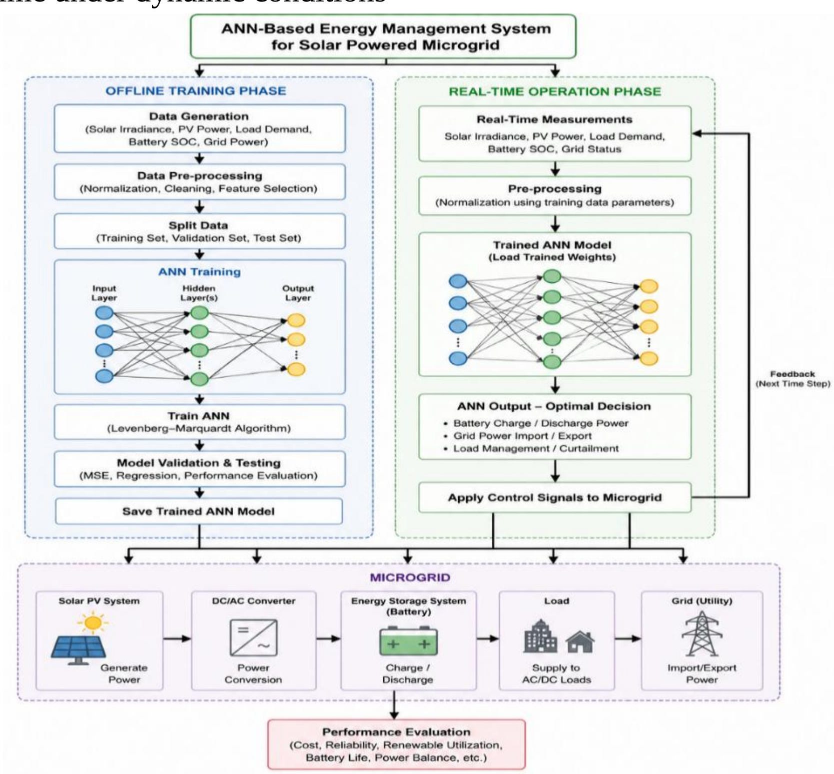

Fig.1. Flow chart.

IV. ANN

The proposed energy management strategy is developed around an Artificial Neural Network (ANN) framework that enables intelligent and adaptive decision-making for renewable-based microgrids operating under highly dynamic conditions. Unlike conventional rule-based or linear control approaches, the ANN-based method captures the nonlinear relationships between renewable generation, load demand, and energy storage behavior, thereby providing a more flexible and accurate control mechanism. In this work, the ANN is designed as a data-driven model that learns optimal energy dispatch patterns from a wide range of operating scenarios generated in the MATLAB/Simulink environment.

The development of the ANN model begins with the creation of a comprehensive dataset representing the microgrid's operational variability. This dataset incorporates fluctuations in solar photovoltaic output due to changing irradiance, variations in wind power caused by stochastic wind speed, dynamic load profiles reflecting real consumption patterns, and different battery state-of-charge conditions. By exposing the ANN to such diverse scenarios, the model becomes capable of generalizing and making reliable decisions even under uncertain and unseen conditions. Prior to training, the dataset is preprocessed through normalization to ensure numerical stability and to improve convergence during the learning phase.

The ANN architecture is implemented as a multilayer feedforward network, which is well-suited for function approximation problems in energy systems. The input layer receives real-time system variables, including renewable power generation, load demand, and battery state of charge, while one or more hidden layers extract complex nonlinear features through weighted connections and activation functions. The output layer produces control signals corresponding to optimal power allocation decisions, such as battery charging or discharging commands and grid power utilization. The network is trained using a supervised learning approach, where target outputs are derived from optimal or near-optimal operating conditions obtained through simulation or prior optimization techniques.

During the training phase, the network weights are iteratively adjusted using the Levenberg–Marquardt backpropagation algorithm, which is known for its fast convergence and high accuracy in nonlinear regression problems. The training process continues until the error between predicted and target outputs is minimized and the network demonstrates strong generalization capability, as verified through validation and testing datasets. Performance indicators such as mean square error and regression coefficients are used to evaluate the quality of the trained model. Care is taken to avoid overfitting by monitoring validation performance and ensuring that the model retains its predictive capability for unseen data.

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Once trained, the ANN is deployed within the real-time control framework of the microgrid. In operation, the network receives instantaneous measurements of system variables and produces immediate control decisions without the need for iterative optimization. This significantly reduces computational burden and enables fast response to sudden changes in renewable generation or load demand. The ANN effectively prioritizes the use of renewable energy, manages battery charging and discharging cycles, and determines when grid support is required, thereby maintaining a balance between energy supply and demand while optimizing overall system performance.
A key advantage of the proposed ANN-based approach lies in its ability to handle uncertainty and variability inherent in renewable energy systems. By learning from historical and simulated data, the network implicitly captures system dynamics and adapts to changing conditions in real time. This results in improved stability, enhanced utilization of renewable resources, and more efficient battery management compared to conventional control strategies. Furthermore, the integration of the ANN within the MATLAB/Simulink platform allows seamless simulation and validation of the proposed method, providing a practical and scalable solution for advanced microgrid energy management in real-world applications.

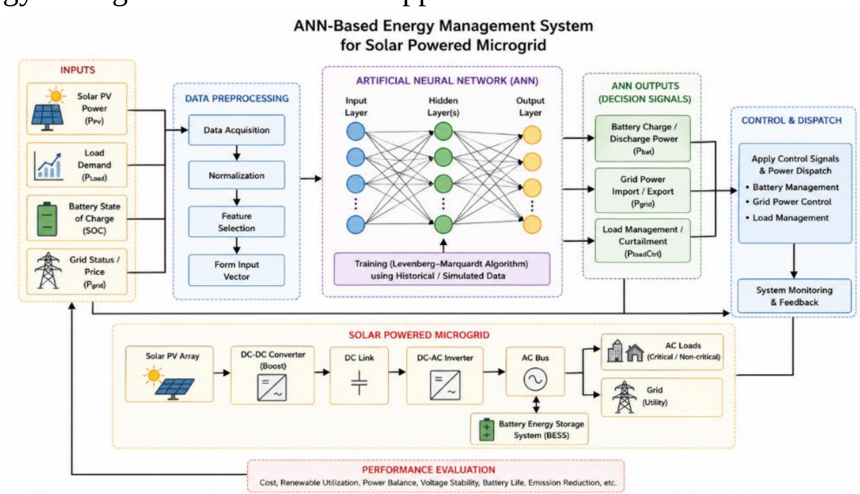

Fig.2. Block diagram

V. MATHEMATICAL FORMULATION

Power Balance Equation

$$P_{pv} + P_{wind} + P_{bess} + P_{grid} = P_{load} + P_{loss}$$

Where P_{pv} is solar power,
P_{wind} is wind power,

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P_bess is battery power,
P_grid is grid power,
P_load is load demand, and
P_loss is system losses.

Objective Function

$$F = w1*C\_op + w2*C\_em + w3*DeltaP$$

Where F is objective function, w1, w2, w3 are weights,
C_op is operational cost,
C_em is emission cost, and
DeltaP is power deviation.

Battery SOC

$$SOC(t) = SOC(t-1) + (P\_charge - P\_discharge)/Capacity$$

Where
SOC(t) is current SOC,
SOC(t-1) is previous SOC,
P_charge is charging power,
P_discharge is discharging power,
Capacity is battery capacity.

SOC Constraints

$$SOC\_min <= SOC <= SOC\_max$$

Where
SOC_min is minimum SOC and
SOC_max is maximum SOC.

ANN Input

$$X = [P\_pv, P\_wind, P\_load, SOC]$$

Where
X is input vector including solar, wind, load and SOC.

ANN Output

$$Y = [P\_bess, P\_grid, Load\_control]$$

Where
Y is output vector including battery, grid and load control signals.

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ANN Model

$$Y = f(W*X + b)$$

Where

W is weight matrix, b is bias and f is activation function.

Error Function

$$E = (1/n) * sum((Y\_actual - Y\_predicted)^2)$$

Where

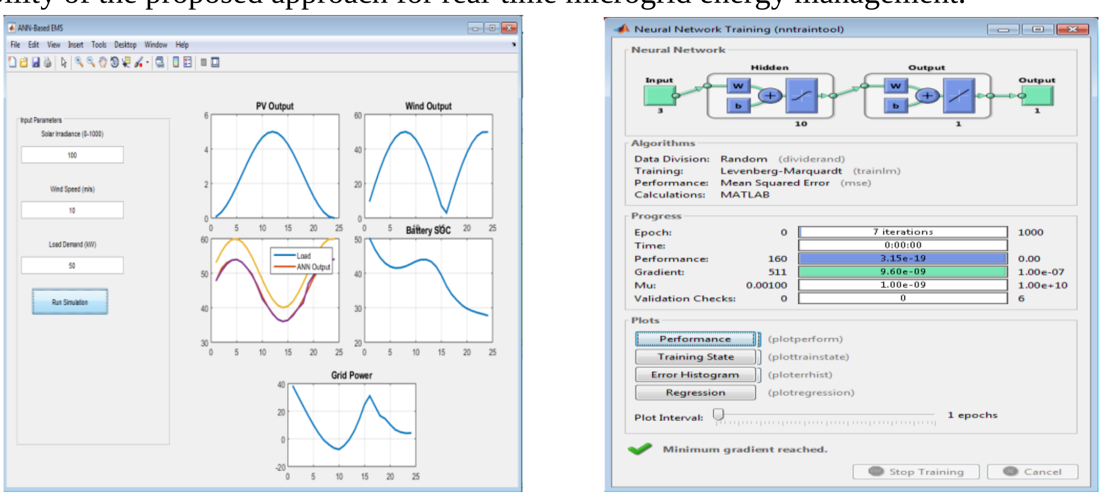
E is mean square error, n is number of samples,

Y_actual is actual output and

Y_predicted is predicted output.

VI. RESULT AND SIMULATION

The simulation of the proposed ANN-based Energy Management System (EMS) for a renewable-based microgrid was carried out under varying load and environmental conditions. The results show that the intelligent control strategy effectively balances power between photovoltaic (PV), wind, battery energy storage system (BESS), and the grid. The ANN model provides accurate forecasting, leading to optimal scheduling of resources and improved battery utilization. Compared to conventional methods and grid dependency, while maintaining voltage stability and enhancing overall power quality. These outcomes confirm the effectiveness and reliability of the proposed approach for real-time microgrid energy management.



(a) (b)

Fig.3. (a) Analysis Input parameters and ANN Predicted Outputs. (b) ANN training Window.

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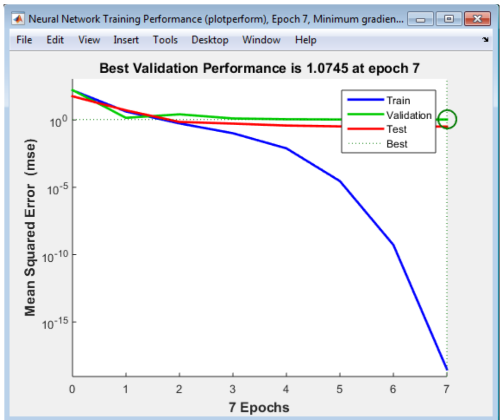
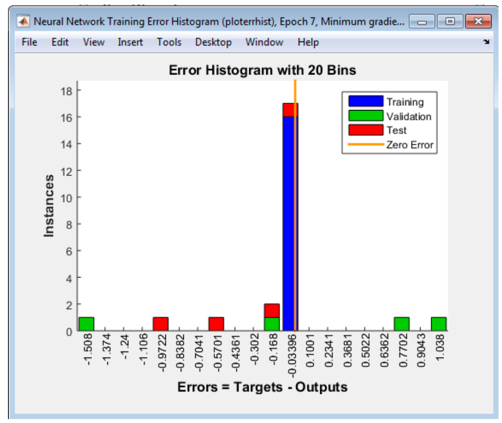
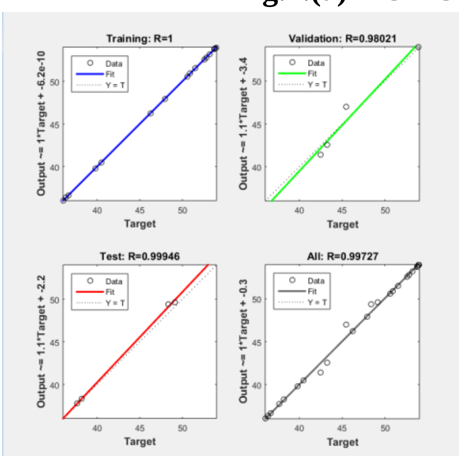
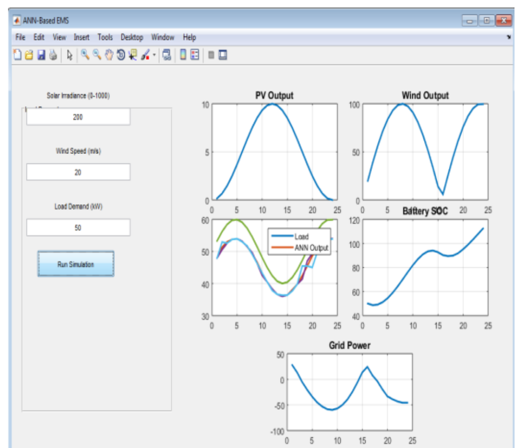




(a) (b)

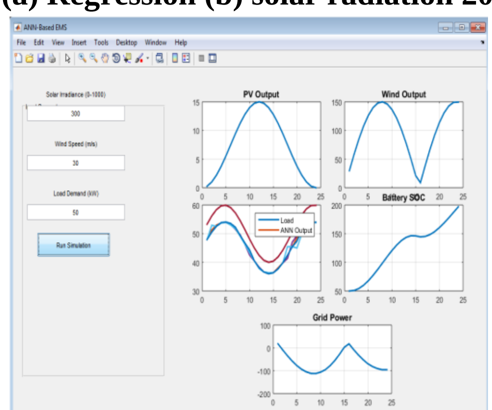
Fig.4.(a) MSE Curve. (b) Error Instance.

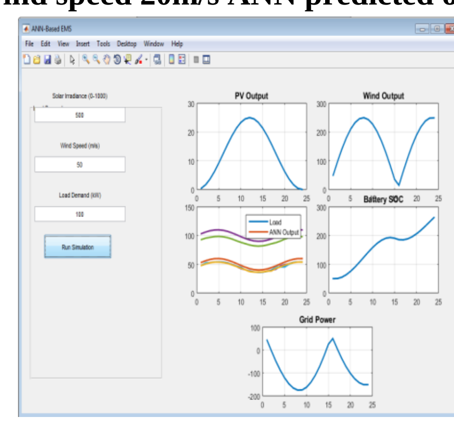




(a) (b)

Fig.5. (a) Regression (b) solar radiation 200 and Wind speed 20m/s ANN predicted outputs.





(a) (b)

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Fig.6.(a) Solar radiation 300 and Wind speed 30m/s ANN predicted outputs. (b) Solar radiation 500 and Wind speed 50m/s ANN predicted outputs.

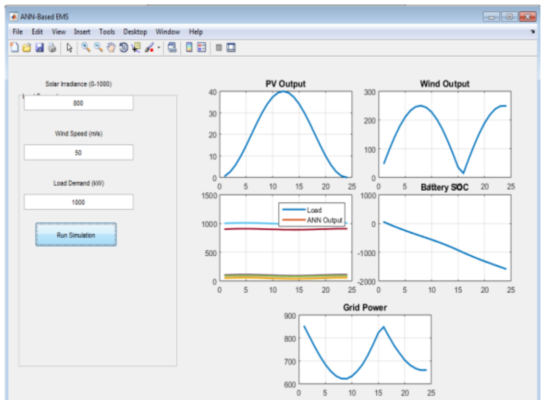

Fig.7.solar radiation 800 and Wind speed 50m/s ANN predicted outputs.

VII. CONCLUSION AND FUTURE SCOPE

Conclusion

The proposed advanced Energy Management System (EMS) based on optimization and Artificial Neural Network (ANN) techniques demonstrates a significant improvement in the operational performance of renewable-based microgrids. By integrating intelligent forecasting with optimized control strategies, the system effectively manages the variability and uncertainty associated with renewable energy sources such as solar and wind. The ANN-based approach enhances prediction accuracy for load demand and generation, enabling better scheduling of energy resources and battery storage. As a result, the system achieves reduced operational cost, minimized power losses, improved power quality, and enhanced system stability. Furthermore, the coordinated control of distributed energy resources ensures reliable power supply with reduced dependence on the utility grid. Overall, the proposed EMS provides a robust, efficient, and scalable solution suitable for modern smart grid applications.

Future Scope

The proposed work can be further extended by incorporating advanced deep learning models such as recurrent neural networks (RNN) and long short-term memory (LSTM) networks for more accurate time-series forecasting of load and renewable generation. Integration of real-time hardware implementation using IoT-enabled sensors and edge computing can enhance the practical applicability of the system. Future research may also explore the use of hybrid optimization techniques, such as combining genetic algorithms with particle swarm optimization, to further improve system efficiency and convergence speed. Additionally, the inclusion of electric vehicles (EVs) and demand response strategies can make the microgrid more flexible and adaptive. Cybersecurity aspects and blockchain-based energy trading mechanisms can also

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be considered to ensure secure and decentralized energy management. Expanding the system to multi-microgrid or community-level energy sharing frameworks will further enhance sustainability and reliability in future smart energy networks.

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