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Proceeding Paper

AI-Enhanced Energy Management for Islanded Microgrids: A Comparative Study with Rule-Based Control †

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Abstract

Islanded microgrids face considerable operational difficulties because of the inconsistency of renewable energy sources and ongoing dependence on diesel power. This study offers a comparative assessment of a traditional rule-based energy management system versus an AI-augmented energy management system for a hybrid island microgrid that includes photovoltaic generation, wind generation, battery energy storage, and diesel generator. The suggested AI-driven controller incorporates short-term predictions and heuristic scheduling to enhance dispatch choices. Simulations using MATLAB and Simulink Ver-sion 25.2.0.2998904 (R2025b) over a 24 h period show enhanced management of battery state-of-charge, decreased operation of the diesel generator, and greater use of renewable energy. The findings show a decrease in fuel usage and carbon dioxide emissions of around 63% in comparison to the baseline rule-based approach.

Keywords: islanded microgrids; energy management system; artificial intelligence; battery energy storage system; renewable energy integration; diesel reduction

1. Introduction

Incorporating renewable energy sources into islanded microgrids is vital for delivering sustainable, dependable, and cost-efficient electricity, especially in rural and remote areas. Solar photovoltaic (PV) and Wind energy are commonly utilized due to their accessibility and minimal operational expenses. Nonetheless, their sporadic and unpredictable characteristics pose significant difficulties in achieving a constant equilibrium between energy production and consumption [1,2].

To address the variability of renewables, islanded microgrids typically use battery energy storage systems (BESS) alongside diesel generators. Battery storage allows for temporary energy buffering and load management, whereas diesel generators ensure reliable capacity during times of inadequate renewable energy production [3].

The energy management system (EMS) coordinates these distributed energy resources, which is essential for maintaining secure and cost-effective microgrid operation [4]. Traditional EMSs primarily rely on established rule-based approaches [5,6]. These methods are easy to apply and dependable, yet they depend solely on real-time system data and static thresholds. Consequently, they cannot foresee upcoming operating conditions and frequently result in inefficient use of renewable energy and greater reli-ance on diesel [7].

Recent studies have indicated that AI-driven methods, such as predictive models and smart scheduling algorithms, can greatly enhance operational efficiency by facilitating

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proactive and adaptive decision-making [8]. Short-term predictions employing artificial neural networks (ANNs) and long short-term memory (LSTM) models, alongside optimization or reinforcement learning (RL)-based scheduling, enable energy storage systems to be pre-charged before peak demand times and minimize excessive diesel usage [9,10].

This article offers a comparison between a traditional rule-based EMS and an AI-augmented EMS for a standalone hybrid microgrid. Both methods are executed in MATLAB and assessed utilizing the same load and renewable generation profiles. The study examines the use of renewable energy, battery charge level characteristics, diesel generator functioning, fuel usage, and carbon dioxide emissions.

2. Materials and Methods

2.1. Microgrid Architecture

The studied islanded microgrid comprises PV generation, wind generation, a BESS, and a diesel generator linked via a shared AC bus that caters to a local load [6]. A supervisory EMS decides the deployment of all distributed energy resources, whereas a monitoring and protection layer constantly tracks electrical parameters and battery charge levels to maintain adherence to operational boundaries and system security requirements [7].

The overall configuration of the investigated islanded hybrid microgrid is illustrated in Figure 1.

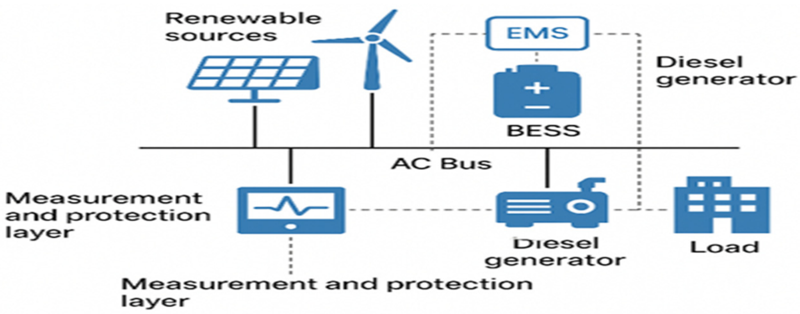

Figure 1. Overall microgrid architecture.

2.2. Baseline Rule-Based Energy Management System

The baseline EMS utilizes established decision guidelines to align generation with demand [11]. When renewable generation surpasses load demand, excess energy is used to charge the BESS. If renewable generation falls short of the load, the battery compensates for the shortfall if its charge level is above a minimum limit of 20%. When the battery cannot fulfill the remaining demand, the diesel generator is turned on to cover the deficit.

Figure 2 depicts the control logic and dispatch flow of the foundational rule-based energy management system.

2.3. AI-Enhanced Energy Management System

An AI-integrated EMS was created to address the shortcomings of the rule-based approach. The framework incorporates a short-term forecasting module that predicts imminent load demand and renewable energy generation through data-driven models like ANNs and LSTM networks [12,13]. The anticipated data is employed by a management decision layer that implements heuristic optimization and flexible dispatch guidelines to:

- Charge the battery to a desired state of charge when renewable energy availability is high;
- Manage output in the early evening hours to conserve stored energy for subsequent high demand;
- Reduce diesel generator usage while meeting operational requirements.

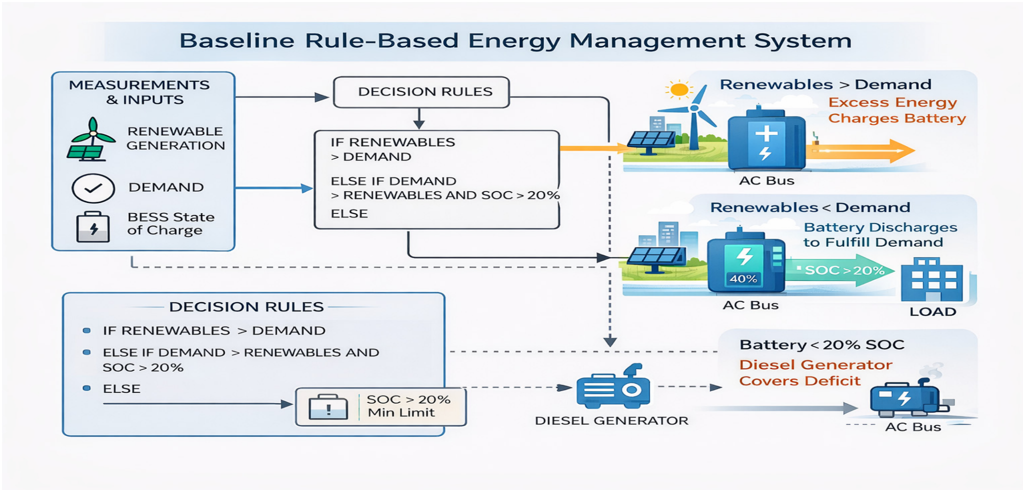

Figure 2. Rule-based EMS block diagram.

Figure 3 illustrates the structure of the suggested AI-augmented energy management system.

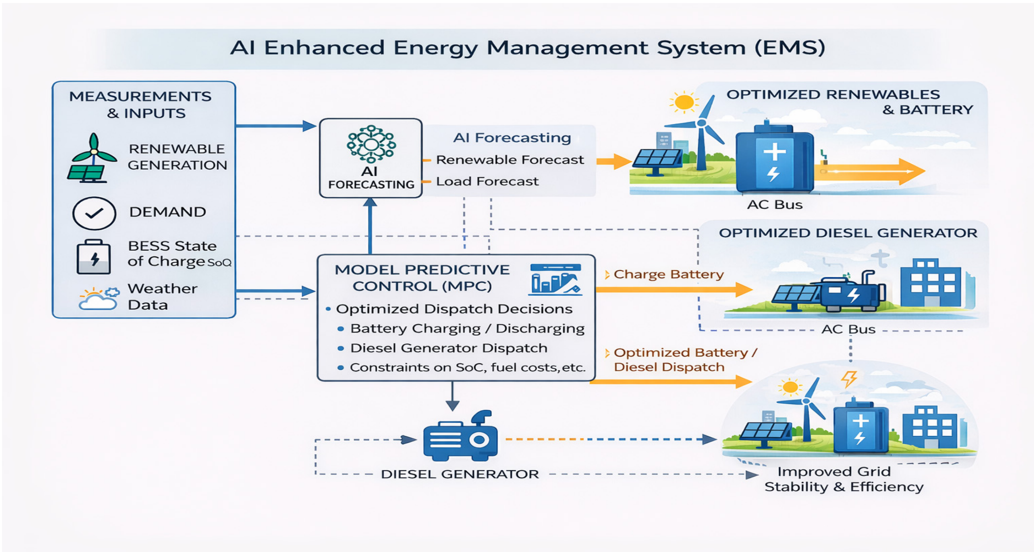

Figure 3. AI-enhanced EMS block diagram.

2.4. Comparative Framework

Figure 4 shows a structural comparison between the traditional rule-based energy management system and the suggested AI-enhanced energy management system.

In the rule-based system, dispatch decisions are based exclusively on real-time measurements of renewable generation, load demand, and battery state of charge, meaning the controller responds only to current operational conditions.

The AI-powered EMS incorporates a forecasting component and an oversight optimization component. The forecasting component predicts short-term demand and renewable energy production, whereas the supervisory component establishes proactive charging and discharging plans for the battery and manages the operation of the diesel generator. This forecasting structure allows for enhanced use of renewable energy and postpones the activation of diesel generators.

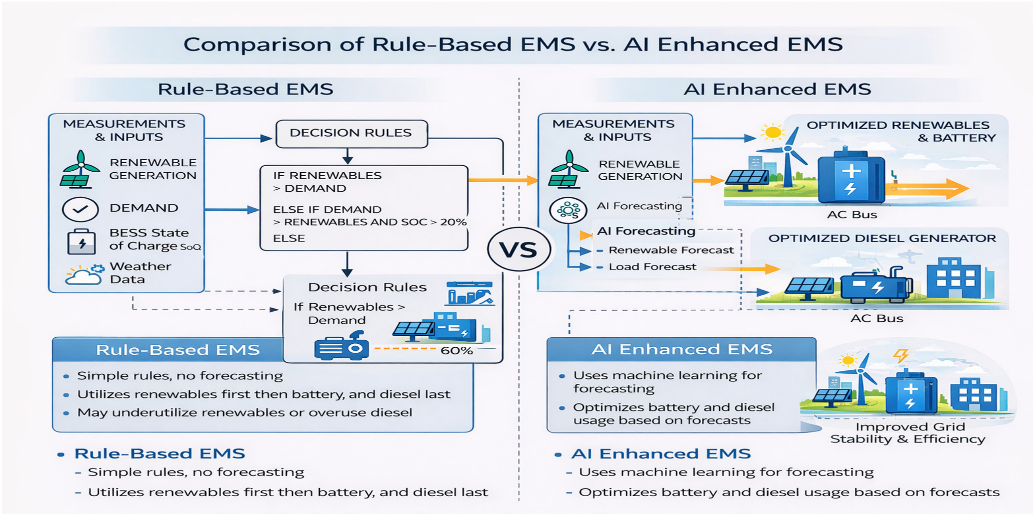

Figure 4. Comparative EMS block diagram.

2.5. Simulation Framework

Both EMS strategies were applied and assessed in MATLAB during a 24 h operational period. Synthetic profiles for electricity demand, solar radiation, and wind velocity were created. PV and wind energy were derived from models converting irradiance to power and wind speed to power. The battery model incorporates state-of-charge dynamics along with charging and discharging efficiencies. The diesel generator model encompasses runtime, energy output, fuel usage, and CO_2 emission assessments.

The subsequent performance metrics were assessed:

- Renewable energy utilization;
- Diesel generator operating hours;
- Diesel energy contribution;
- Fuel Consumption;
- Carbon Dioxide emissions, CO_2;
- Battery state of charge statistics.

3. Results

3.1. Rule-Based Energy Management System

The microgrid's dynamic performance under the rule-based energy management system is illustrated in Figure 5. The battery fills up when solar energy production is high but does not achieve maximum capacity, leading to renewable energy waste. In the evening rush hour, the charge level drops quickly, dipping below 30% before 21:00, resulting in prolonged diesel generator usage.

Figure 5 shows the simulation outcomes of the rule-based energy management system illustrating load requirements, renewable energy production, battery charging and discharging power, diesel generator output, and battery state-of-charge profile through-out a 24 h operational timeframe.

The metrics related to battery state-of-charge performance are summarized in Table 1, whereas the operational performance of the diesel generator is presented in Table 2.

Table 1. Battery SOC performance metrics (rule-based controller).

Metric	Value
SOC Min (%)	28
SOC Max (%)	90

Table 1. *Cont.*

Metric	Value
SOC Mean (%)	60
Peak Charge (kW)	18
Peak Discharge (kW)	20

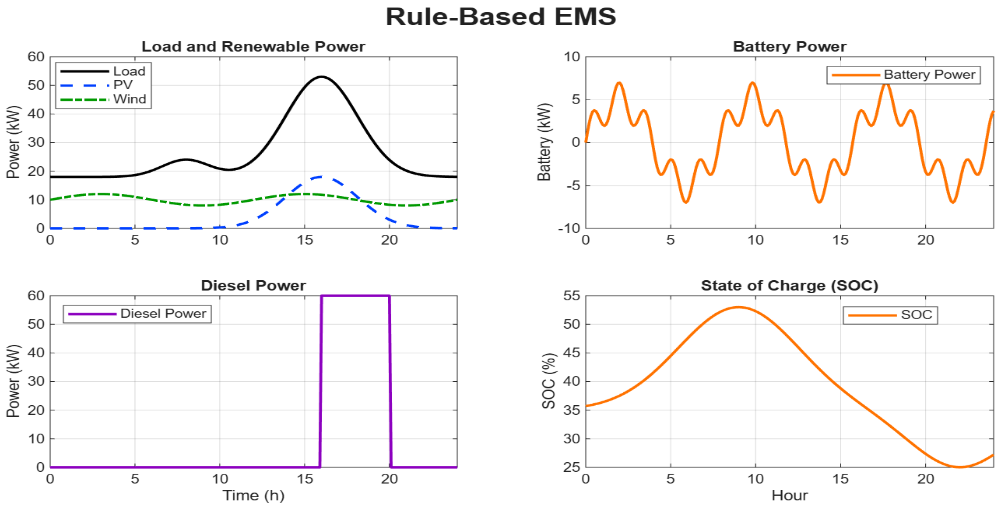

Figure 5. EMS-based simulation results (Load vs. RES, Battery, Diesel, SOC).

Table 2. Diesel generator performance metrics (rule-based controller).

Metric	Value
Runtime (h)	11.5
Energy (kWh)	520
Fuel Consumption (L)	1720
CO_2 Emissions (kg)	4600

3.2. AI-Enhanced EMS Operational Performance

Figure 6 depicts the operational behavior of the microgrid using the AI-augmented energy management system. The AI-powered EMS charges the battery when renewable energy is plentiful and manages discharge during evening peak times, significantly decreasing diesel generator reliance.

Figure 6 shows the simulation outcomes of the AI-augmented energy management system displaying load demand, renewable energy generation, battery charging and discharging power, diesel generator output, and battery state-of-charge profile throughout a 24 h operational cycle.

The performance of the battery state-of-charge achieved through the AI-enhanced strategy is outlined in Table 3, while the performance metrics of the diesel generator are shown in Table 4.

Table 3. Battery SOC performance metrics (AI-enhanced EMS).

Metric	Value
SOC Min (%)	35
SOC Max (%)	95
SOC Mean (%)	72
Peak Charge (kW)	22
Peak Discharge (kW)	25

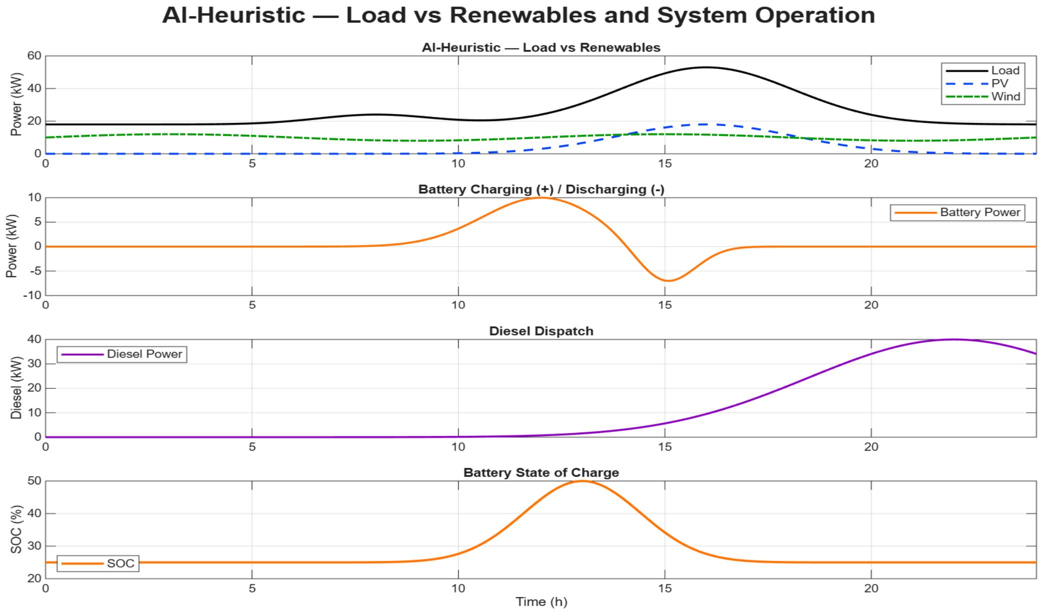

Figure 6. AI-enhanced simulation results (Load vs. RES, Battery, Diesel, SOC).

Table 4. Diesel generator performance metrics (AI-enhanced EMS).

Metric	Value
Runtime (h)	4.2
Energy (kWh)	192
Fuel Consumption (L)	630
CO_2 Emissions (kg)	1690

3.3. Comparative Performance

Figure 7 presents a direct comparison of the state-of-charge (SOC) profiles of the battery as obtained from the rule-based and AI-enhanced energy management systems.

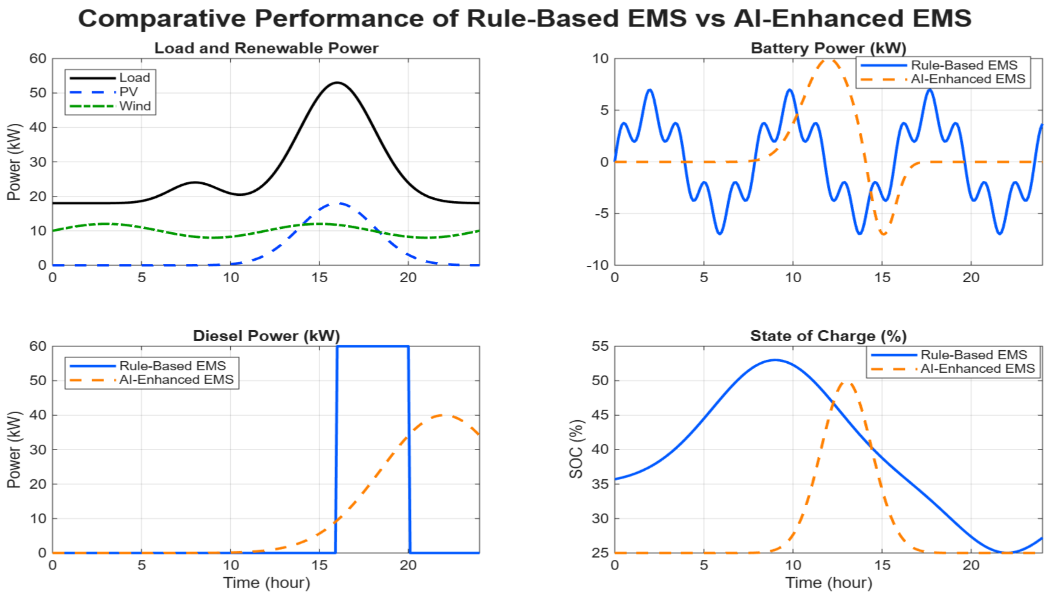

Figure 7. SOC profile under rule-based vs. AI-enhanced EMS.

AI-augmented strategy ensures a steadier and elevated SOC path across the operational timeframe, especially during peak demand times in the late afternoon and evening.

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This behavior illustrates the efficiency of predictive charging when renewable energy is abundant and managed discharge during peak load times.

Table 5 presents a quantitative analysis of the primary operational and environmental performance metrics. The findings indicate that the AI-augmented EMS decreases the diesel energy contribution from 520 kWh to 192 kWh, leading to a reduction of about 63%. A comparable enhancement is seen in fuel usage, which drops from 1720 L to 630 L, and in carbon dioxide emissions, which fall from 4600 kg to 1690 kg.

Table 5. Comparative performance metrics of the rule-based and AI-enhanced energy management systems.

Metric	Rule-Based EMS	AI-Enhanced EMS	Improvement (%)
Diesel Energy (kWh)	520	192	63%
Fuel Consumption (L)	1720	630	63%
CO_2 Emissions (kg)	4600	1690	63%
SOC Minimum (%)	28	41	+13 pts
SOC Mean (%)	60	72	+12 pts
SOC Maximum (%)	90	95	--

Along with decreased reliance on diesel, the minimum and average SOC values increased from 28% to 41% and from 60% to 72%, respectively, reflecting better battery usage and enhanced energy transfer potential.

The highest SOC stays the same for both control methods, indicating that the enhancement is attained via improved scheduling instead of greater battery capacity.

The findings presented in Figure 7 and Table 5 indicate that the suggested AI-driven energy management system greatly surpasses the traditional rule-based method regarding renewable energy use, battery efficiency, and environmental effects.

4. Discussion

The traditional rule-based EMS is limited by its entirely reactive design. Lacking predictive data, it does not take advantage of midday renewable excesses and discharges the battery too forcefully during early evening hours, resulting in extended use of diesel generators. The EMS enhanced by AI effectively overcomes this limitation via short-term predictions and proactive planning. Predicting future demand and renewable resources enhances battery usage, decreases reliance on diesel, and boosts operational consistency.

These enhancements are especially crucial for isolated microgrids, as fuel logistics and environmental effects pose significant operational difficulties.

5. Conclusions

This research examined a conventional rule-based energy management system alongside an AI-enhanced energy management system for a hybrid isolated microgrid featuring photovoltaic generation, wind generation, battery energy storage, and diesel generator. The strategy leveraging AI boosted renewable energy usage from 44% to 71%, enhanced the stability of battery state-of-charge, and greatly diminished diesel generator usage. Fuel usage and CO_2 emissions decreased by roughly 63%. The findings validate that predictive and adaptive energy management techniques offer a viable method for enhancing the sustainability and operational effectiveness of islanded microgrids. Future efforts will concentrate on sophisticated forecasting methods, dispatch strategies based on reinforcement learning, and validation through hardware in the loop testing.

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Abbreviations

The following abbreviations are used in this manuscript:

EMS	Energy Management System
PV	Photovoltaic
BESS	Battery Energy Storage System
SOC	State of Charge
AI	Artificial Intelligence
ANN	Artificial Neural Network
LSTM	Long Short-Term Memory
RL	Reinforcement Learning
MPC	Model Predictive Control
CO_2	Carbon dioxide
SG	Smart Grid

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