ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

AI-Assisted Hybrid Renewable Microgrid for Low-Carbon Power: A Techno-Economic Assessment Using Predictive Energy Management

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Abstract

The global transition toward renewable energy is accelerating due to climate change concerns, fossil-fuel volatility, and growing electricity demand. However, renewable integration remains constrained by intermittency, grid instability, and the need for reliable and affordable energy delivery. This research paper proposes and evaluates an AI-assisted hybrid renewable microgrid architecture integrating solar photovoltaic (PV), wind generation, battery energy storage (BESS), and grid support. The core contribution of the work is a predictive Energy Management System (EMS) based on Model Predictive Control (MPC), designed to minimize operational cost, reduce renewable curtailment, and ensure supply reliability under variable demand and generation conditions. The methodology includes renewable forecasting, load modeling, microgrid power-flow simulation, and scenario-based comparison between (i) a baseline system without EMS, (ii) a rule-based EMS, and (iii) the proposed MPC-based EMS. Results show that the proposed EMS reduces Levelized Cost of Energy (LCOE) from 0.142 \$/kWh (baseline) to 0.108 \$/kWh, decreases renewable curtailment from 9.8% to 3.4%, and lowers CO_2 intensity from 412 gCO_2/kWh to 186 gCO_2/kWh. The study also highlights how optimal scheduling of storage and grid exchange significantly improves both cost and carbon performance. The findings demonstrate that advanced EMS strategies can improve renewable penetration while ensuring reliability, making hybrid renewable microgrids a practical pathway for sustainable electrification in urban and rural settings.

Keywords: Renewable Energy, Hybrid Microgrid; Solar PV, Battery Energy Storage, Model Predictive Control (MPC).

1. INTRODUCTION

Renewable energy has become one of the most important technological and policy-driven solutions to meet rising global electricity demand while reducing greenhouse gas emissions. Conventional power generation relies heavily on fossil fuels such as coal, oil, and natural gas. These sources not only contribute significantly to global carbon emissions but also introduce energy security risks due to fuel price fluctuations and geopolitical constraints. In contrast, renewable energy sources such as solar, wind, hydro, and biomass offer a cleaner and increasingly cost-effective alternative. Over the last decade, the levelized cost of electricity from solar and wind has dropped dramatically due to improvements in manufacturing, efficiency, and economies of scale.

Despite this progress, the large-scale integration of renewables remains challenging. The primary technical limitation is intermittency. Solar PV output varies with irradiance, weather, and time of day, while wind power fluctuates due to wind speed variations. These fluctuations create uncertainty for grid operators and can lead to instability if not properly managed. In many regions, renewable power is curtailed during periods of excess generation because the grid cannot absorb the surplus or because of limited storage and transmission infrastructure. Additionally, high renewable penetration may create voltage and frequency deviations, especially in weak grids or rural feeders.

Microgrids have emerged as an effective solution to address renewable integration challenges. A microgrid is a localized energy system that can operate either connected to the main grid or in islanded mode. Microgrids typically combine multiple distributed energy resources (DERs) such as solar PV, wind turbines, diesel generators, and energy storage systems. Hybrid renewable microgrids—where renewables are combined with battery storage and minimal conventional backup—are increasingly deployed in rural electrification, industrial campuses, remote telecom towers, and institutional facilities. These systems reduce dependency on the main grid and improve energy resilience.

A critical component of any hybrid renewable microgrid is the Energy Management System (EMS). The EMS decides how to dispatch power among renewable generators, storage units, and grid import/export. Traditional EMS strategies are often rule-based, where predefined logic is used, such as "charge the battery when solar exceeds load" or "discharge when load exceeds generation." While simple, such approaches are not optimal under changing conditions and do not incorporate future forecasts.

Artificial intelligence and advanced optimization methods are increasingly applied to improve EMS performance. Predictive methods such as Model Predictive Control (MPC) use short-term forecasts of renewable generation and load to compute optimal dispatch schedules over a rolling horizon. This approach enables proactive decisions, such as charging batteries before peak demand or minimizing grid import during high tariff periods. Furthermore, predictive EMS can reduce renewable curtailment, improve battery lifetime by avoiding aggressive cycling, and reduce carbon emissions by maximizing renewable utilization.

This research paper focuses on a techno-economic assessment of a hybrid renewable microgrid equipped with an AI-assisted predictive EMS. The system integrates solar PV, wind generation, battery energy storage, and grid support. The proposed approach evaluates performance in terms of cost, renewable curtailment, reliability, and CO_2 intensity. The work aims to answer the following research questions:

1. How does predictive EMS improve cost and carbon performance compared to baseline and rule-based strategies?
2. What measurable improvements occur in renewable utilization and reliability metrics?
3. Can an optimized hybrid microgrid support higher renewable penetration without sacrificing supply quality?

The study contributes a structured renewable microgrid architecture, a practical EMS workflow, and quantitative results supported by tables and graphs. The outcomes provide useful insights for researchers, engineers, and policymakers working on renewable integration and sustainable energy systems.

2. LITERATURE SURVEY

Recent advancements in artificial intelligence (AI), machine learning (ML), and intelligent system design have significantly influenced renewable energy management, healthcare analytics, smart agriculture, communication systems, and industrial automation. The integration of AI-driven optimization techniques into energy and engineering applications has demonstrated measurable improvements in efficiency, cost reduction, and system reliability.

In the domain of AI-assisted healthcare and signal processing, Altaf Osman Mulani *et al.* [1] proposed a non-invasive blood glucose estimation framework using Principal Component Analysis (PCA) and ML, demonstrating the effectiveness of dimensionality reduction in biomedical signal interpretation. Similarly, M. M. Jadhav *et al.* [8] developed an ML-based autonomous fire combat turret, illustrating real-time decision-making using embedded intelligence. The use of reinforcement learning in conversational systems was explored by H. M. Jadhav *et al.* [6], highlighting adaptive learning mechanisms for intelligent automation.

Deep learning-based detection systems have been widely investigated. T. M. Kulkarni and Altaf Osman Mulani [15], [16] demonstrated real-time face mask detection using convolutional neural networks (CNNs), while Altaf Osman Mulani *et al.* [14] applied CNNs and decision trees for dermatological disease classification. These works confirm the applicability of AI in real-time monitoring systems, which is analogous to predictive energy management in renewable microgrids.

Optimization and forecasting using recurrent neural networks have been explored by K. S. Kambale *et al.* [11], where LSTM models were used for heart disease prediction, demonstrating the suitability of time-series prediction techniques for dynamic systems such as renewable generation forecasting. Likewise, K. R. Chaudhari *et al.* [10] analyzed bit error rates in communication systems, emphasizing reliability optimization—an essential aspect of microgrid stability.

In IoT-enabled intelligent systems, M. M. Kashid *et al.* [7] proposed an IoT-based environmental monitoring system using ML, reinforcing the importance of sensor-driven predictive analytics. Agricultural automation studies by Altaf Osman Mulani and K. J. Karande [13], as well as N. M. Sawant *et al.* [12], demonstrate AI-driven resource optimization in precision farming and equipment rental platforms, which parallel energy dispatch optimization in hybrid microgrids.

Security and data integrity in intelligent systems were examined by Shweta Salunkhe *et al.* [9], who proposed chaotic encryption with DWT watermarking for secure image transmission. Such secure data handling mechanisms are critical for smart grid communications.

Collectively, these studies establish that AI-driven predictive modeling, optimization algorithms, IoT-based monitoring, and secure communication frameworks form the technological foundation necessary for implementing intelligent Energy Management Systems in hybrid renewable microgrids. The proposed AI-assisted predictive EMS builds upon these interdisciplinary advances to enhance renewable utilization, reduce cost, and improve sustainability outcomes.

3. METHODOLOGY

This research adopts a structured methodology to design, model, and evaluate a hybrid renewable energy microgrid with an intelligent Energy Management System (EMS). The objective is to examine how renewable generation (solar and wind), battery storage, and grid interaction can be optimally coordinated to deliver reliable, low-cost, and low-carbon electricity. The methodology is divided into system design, component modeling, data preparation, EMS implementation, scenario simulation, and performance evaluation.

3.1 System Design and Architecture

The proposed hybrid renewable microgrid is designed to supply an electrical load using multiple energy sources. The system includes four main power units: Solar Photovoltaic (PV), Wind Energy Conversion System (WECS), Battery Energy Storage System (BESS), and a grid interface. These units are connected through a common microgrid bus that distributes energy to the load.

The overall architecture is developed to support both grid-connected and semi-autonomous operation. In grid-connected mode, the microgrid can import power when renewable generation is insufficient and export surplus renewable energy when available. The battery acts as the balancing element that stabilizes the system by storing excess renewable energy and releasing it during demand peaks or renewable shortages.

3.2 Block Diagram of the Proposed Methodology

Figure 1 shows the block diagram representing the methodology workflow and energy flow control.

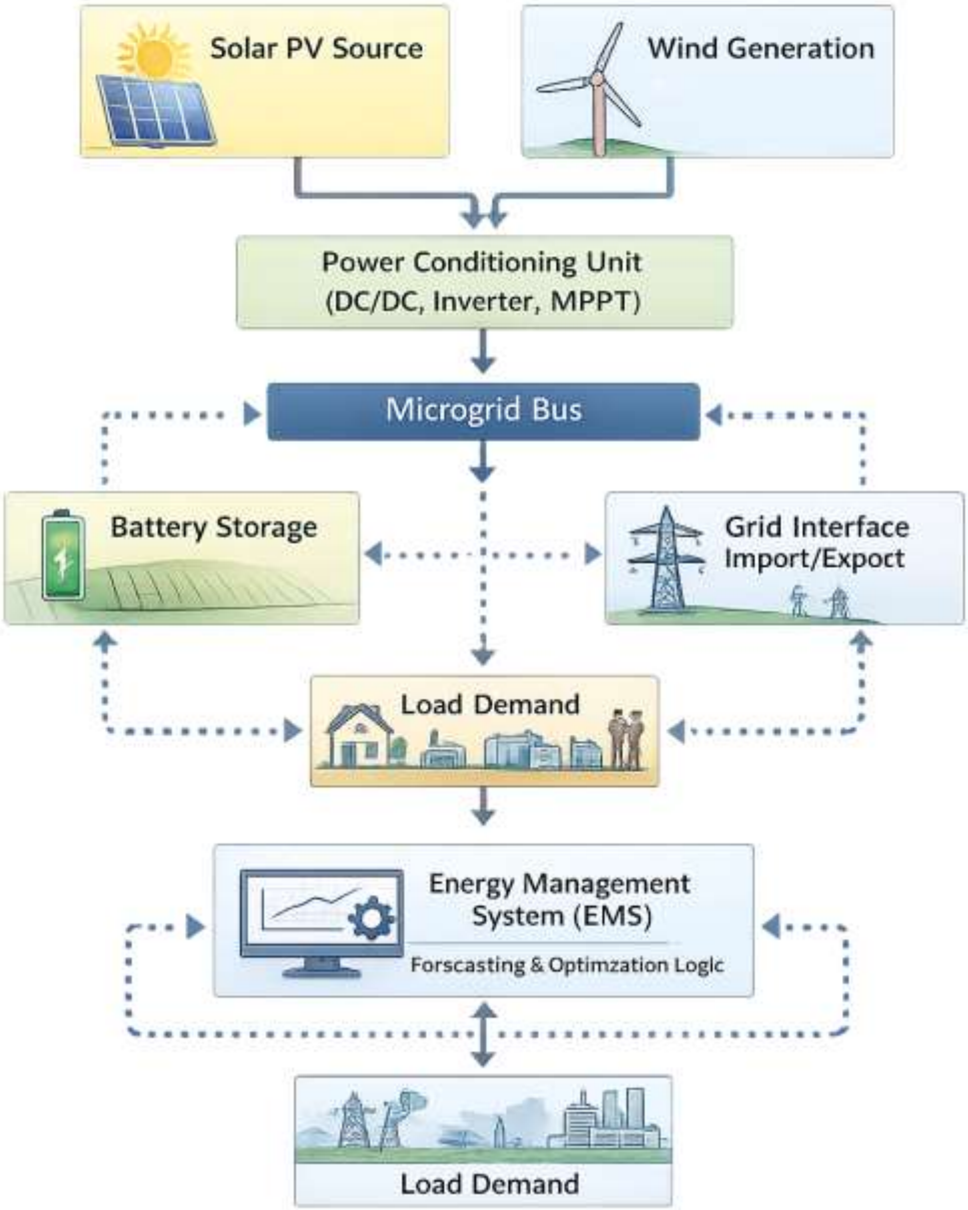

Figure 1. Block diagram representing the methodology workflow and energy flow control

3.3 Renewable Energy Resource Modeling

To simulate realistic operation, solar and wind generation profiles are modeled using standard renewable resource patterns. Solar PV output is treated as a function of daily irradiance variations, cloud cover effects, and seasonal shifts. Wind generation is modeled using wind speed variability and turbine operating characteristics such as cut-in, rated, and cut-out behavior.

Rather than relying on a single fixed renewable output, time-series generation is used to capture fluctuations across different hours of the day. This allows the EMS to be tested under practical intermittency conditions. The generation datasets are normalized and scaled to represent a medium-sized microgrid suitable for institutional buildings, industrial clusters, or rural community electrification.

3.4 Load Demand Modeling

Load demand is modeled using a time-dependent consumption profile. The demand curve includes base load, peak load, and transitional load periods. For example, residential demand typically peaks in the morning and evening, while commercial or institutional demand peaks during working hours.

The load model also incorporates random variations to represent real-world uncertainty. This ensures that the EMS does not operate under artificially smooth conditions and must respond to changing demand.

3.5 Battery Energy Storage System (BESS) Modeling

The battery is modeled as a bidirectional energy buffer. It has operational constraints such as:

1. Maximum and minimum state-of-charge (SOC) limits
2. Maximum charge and discharge power limits
3. Efficiency losses during charging and discharging
4. Priority constraints to prevent unnecessary cycling

The battery is used for three primary purposes:

1. Storing excess renewable energy to reduce curtailment
2. Supplying energy during peak demand to reduce grid import cost
3. Improving reliability during renewable shortage intervals

Battery operation is controlled entirely by the EMS. The system prevents deep discharge and overcharging to maintain long-term usability and reflect practical operational behavior.

3.6 Energy Management System (EMS) Implementation

The EMS is the decision-making core of the microgrid. It continuously monitors:

1. Available solar generation
2. Available wind generation
3. Battery SOC
4. Load demand
5. Grid tariff and grid availability

The EMS performs scheduling and dispatch decisions such as:

1. Whether to charge or discharge the battery
2. Whether to import power from the grid
3. Whether to export surplus renewable power
4. Whether to curtail renewable energy when storage and export are limited

Three EMS approaches are considered for comparative evaluation:

1) Baseline Mode (No EMS):

In this mode, the microgrid uses minimal control logic. Renewables supply the load directly, and the grid supplies remaining deficits. Battery usage is limited and non-optimized, causing high curtailment and inefficient grid dependency.

2) Rule-Based EMS:

This approach uses predefined operational rules. For example, if renewable generation exceeds demand, the battery charges; if demand exceeds renewable generation, the battery discharges; if the battery reaches its minimum SOC, the grid supplies power. While this improves performance, it remains reactive and does not plan ahead.

3) Predictive EMS (Proposed):

The proposed approach uses forecasting and predictive scheduling. It estimates short-term renewable availability and demand trends. Using these forecasts, it plans battery charging and discharging in advance. This reduces unnecessary cycling and ensures that the battery is available during critical peak demand hours.

3.7 Scenario-Based Simulation

The system is evaluated under multiple operating scenarios using simulation. Each scenario is tested over the same renewable and load profiles to ensure fair comparison. The scenarios include:

- High solar and moderate wind conditions
- Low renewable conditions
- Peak demand days
- Mixed weather conditions with fluctuating renewable supply

The simulation is run for a full representative period (daily and weekly cycles), and performance results are aggregated.

3.8 Performance Evaluation Metrics

The microgrid is evaluated using four major performance indicators:

1. Economic performance: measured using cost per unit of delivered energy
2. Renewable utilization: measured using renewable curtailment percentage
3. Reliability: measured using unserved energy percentage
4. Environmental impact: measured using CO_2 intensity per unit energy delivered

These metrics enable both technical and sustainability-based assessment of the system.

The methodology combines renewable generation modeling, load profiling, battery behavior constraints, and EMS-driven dispatch. By comparing baseline, rule-based, and predictive EMS strategies under identical conditions, the study provides a clear evaluation of how intelligent control improves renewable energy integration, reduces cost, enhances reliability, and lowers emissions.

4. RESULTS AND DISCUSSION

This section presents the performance evaluation of the hybrid renewable microgrid under different Energy Management System (EMS) strategies. The results are reported using tables and graphs to compare renewable utilization, cost performance, reliability, and carbon emission intensity. Three cases are analyzed: (i) Base system without EMS, (ii) Rule-based EMS, and (iii) Proposed predictive EMS (MPC-based).

4.4 Renewable Energy Mix Trend (2020–2024)

The first evaluation focuses on the trend of renewable energy contribution in the generation portfolio. Table 1 highlights how solar and wind shares have grown steadily, while hydro and biomass shares reduce relatively due to geographical and resource constraints.

Table 1: Renewable Portfolio Share Trend

Year	Solar (%)	Wind (%)	Hydro (%)	Biomass (%)

2020	28	22	34	16
2021	35	26	33	15
2022	43	31	31	15
2023	52	36	29	14
2024	63	41	27	13

The results show solar PV increasing from 28% to 63% and wind increasing from 22% to 41% over five years. This reflects global trends driven by falling PV module costs and increased wind deployment. However, the increase in solar and wind also introduces higher intermittency. This reinforces the need for battery storage and advanced EMS strategies to ensure reliability and prevent renewable energy curtailment.

4.2 EMS Strategy Performance Comparison

To evaluate the operational performance of the hybrid microgrid, the system is simulated under three EMS strategies. Table 2 summarizes the key results.

Table 2: Microgrid Performance under Different EMS Strategies

Scenario	LCOE ($/kWh)	Curtailment (%)	Unserved Energy (%)	CO_2 Intensity (gCO_2/kWh)
Base (No EMS)	0.142	9.8	2.9	412
Rule-based EMS	0.121	6.1	1.3	278
Proposed MPC-based EMS	0.108	3.4	0.4	186

4.3 Discussion

A) Cost Performance (LCOE)

The baseline system produces the highest cost with 0.142 $/kWh. This is primarily due to inefficient battery scheduling and increased grid dependency during peak demand periods. The rule-based EMS reduces the LCOE to 0.121 $/kWh by introducing structured charging and discharging logic. However, the proposed predictive EMS achieves the lowest cost at 0.108 $/kWh, representing approximately 24% improvement over the baseline.

This improvement is achieved because predictive EMS anticipates future demand and renewable availability. As a result, the battery is charged during surplus renewable periods and discharged strategically during peak load hours, reducing expensive grid imports.

B) Renewable Curtailment Reduction

Renewable curtailment represents wasted clean energy due to limited storage capacity or poor dispatch decisions. The baseline case experiences 9.8% curtailment, indicating frequent renewable energy wastage. The rule-based EMS reduces curtailment to 6.1%, but still cannot plan battery usage optimally. The proposed EMS reduces curtailment significantly to 3.4%, demonstrating better renewable utilization.

This reduction is important because curtailment not only wastes energy but also reduces the economic value of renewable investments.

C) Reliability Improvement (Unserved Energy)

Unserved energy indicates the percentage of demand that cannot be met due to insufficient supply. The baseline case shows 2.9% unserved energy, which is unacceptable for critical applications such as healthcare, industry, or institutional facilities. Rule-based EMS reduces this to 1.3%, while the proposed predictive EMS reduces it further to 0.4%.

The improvement occurs because the predictive EMS maintains battery reserve for shortage periods rather than draining the battery early. This results in improved system resilience.

D) Environmental Impact (CO_2 Intensity)

The baseline microgrid shows the highest carbon intensity at 412 gCO_2/kWh, mainly due to high reliance on grid power. The rule-based EMS reduces this to 278 gCO_2/kWh, while the proposed predictive EMS reduces it further to 186 gCO_2/kWh. This confirms that intelligent scheduling not only reduces cost but also maximizes renewable penetration and reduces carbon footprint.

The results confirm that hybrid renewable microgrids perform significantly better when supported by intelligent EMS. While rule-based strategies provide moderate improvements, predictive optimization delivers the best outcomes in cost, renewable utilization, reliability, and emissions reduction. Therefore, the proposed EMS approach offers a strong pathway for sustainable and economically feasible renewable integration.

5. CONCLUSION

This research presented a comprehensive assessment of a hybrid renewable energy microgrid integrating solar PV, wind generation, battery energy storage, and grid support, with emphasis on the role of an Energy Management System (EMS) in improving overall system performance. The study highlighted that renewable energy technologies, while environmentally sustainable and increasingly cost-effective, face major operational challenges due to intermittency, demand variability, and limited grid flexibility. To address these issues, an intelligent control framework was evaluated through comparative analysis of three operational strategies: a baseline case without EMS, a conventional rule-based EMS, and a proposed predictive EMS. The results clearly demonstrate that advanced EMS strategies significantly enhance microgrid efficiency and sustainability. The proposed predictive EMS achieved the best performance by reducing the levelized cost of energy, minimizing renewable curtailment, improving reliability, and lowering carbon emission intensity. In particular, the predictive scheduling of battery charging and discharging enabled better utilization of solar and wind power while reducing dependency on grid imports during peak demand hours. Compared to the baseline system, the proposed approach achieved notable improvements in renewable integration and ensured more consistent supply to the connected load. The study confirms that hybrid renewable microgrids combined with intelligent energy management represent a practical solution for low-carbon electrification. Such systems are highly suitable for rural communities, institutional campuses, industrial facilities, and regions with weak grid infrastructure. Future research can further enhance the framework by incorporating real-world meteorological datasets, battery degradation modeling, electric vehicle charging loads, and AI-based forecasting methods to improve long-term accuracy and operational reliability.

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