

Article

Optimized Energy Management and Reliability Assessment of RES Based Microgrid

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Abstract

This paper describes the optimized energy management and a reliability assessment of a renewable energy source (RES)-based microgrid comprising solar photovoltaic (PV), wind, battery storage, and fuel cell systems. This study evaluates system performance under 16 operating scenarios. Reliability indices such as loss of load expectation (LOLE), loss of load probability (LOLP), and expected energy not supplied (EENS) are computed for three configurations: without an energy management system (EMS), with an EMS, and with an optimized EMS. The integration of an EMS significantly improves system reliability by reducing supply interruptions and energy curtailment from 83.3% to 95.3%. Furthermore, applying optimal scheduling in conjunction with an EMS reduces costs by 68.49% per hour compared with a standalone EMS.

Keywords: microgrid; energy management system; reliability analysis; loss of load expectation; expected energy not supplied; renewable energy; battery energy storage; power systems; fault tolerance; distributed generation

1. Introduction

To meet the global energy demand while reducing carbon emissions, renewable energy resources are increasingly being integrated into microgrids. Microgrids enable local energy generation with reduced transmission losses and improved energy access in remote areas. However, significant reliability challenges arise due to the variability in and uncertainty of solar and wind generation, and these issues must be assessed [1].

Reliability assessments of power systems traditionally rely on probabilistic methods; however, for microgrids, these methods must be extended to capture the behavior of generation, load, and storage elements [2].

Energy management systems (EMSs) play a vital role in coordinating microgrid resources. They can reduce energy curtailment and improve reliability [3].

This work addresses the above gap by evaluating three configurations: (i) without an EMS, (ii) with an EMS, and (iii) with an EMS with optimal scheduling. The contributions of this work include enumerating common failure scenarios, computing LOLE, LOLP, and EENS for each configuration, and reducing operating cost through optimization.

The remainder of this paper is organized as follows: Section 2 reviews the background literature. Section 3 describes the microgrid system considered in this study. Section 4 presents the EMS framework. Section 5 describes the reliability assessment methodology. Section 6 discusses the results for all three configurations. Section 7 concludes this paper.



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2. Background

Reliability assessment metrics for conventional power systems are well-documented [4]. Billinton and Allan [5] provided a framework for generation adequacy evaluation, which has been extended to microgrids with RESs.

IEEE Std. 2030.7-2017 specifies microgrid controller requirements [6]. Guerrero et al. [7] discussed hierarchical control of droop-controlled AC and DC microgrids. Parisio et al. [8] performed MPC-based microgrid optimization. IEEE Std. 1366-2012 defines electric power distribution reliability indices [9]. Che et al. [10] developed a hierarchical coordination framework for integrated AC/DC community microgrids. Morstyn et al. [11] analyzed power sharing and stability in microgrids with distributed storage, and Keane et al. [12] presented planning and optimization techniques for distributed generation.

Billinton and Li [13] established foundational Monte Carlo methods for power system reliability assessments. Foruzan et al. [14] proposed a reinforcement learning approach for optimal distributed energy management in a microgrid.

Govindarajan et al. [15] proposed a deep-learning-based forecasting model to capture nonlinear relationships between meteorological variables and PV output and thereby improve forecasting accuracy.

Pinson and Kariniotak [16] developed conditional prediction intervals for wind power forecasting. Govindarajan et al. [17] suggested a deep learning framework that improves prediction accuracy by capturing nonlinear characteristics of wind data. Liu et al. [18] highlighted critical cybersecurity weaknesses in smart grid energy management systems. Metke and Ekl [19] proposed security frameworks for smart grid networks.

However, few studies have evaluated the incremental benefit of moving from a standard EMS to a fully optimized EMS in terms of standard reliability indices under explicitly enumerated failure scenarios. Nargeszar et al. [20] primarily focused on probabilistic reliability evaluation under dynamic operating conditions using Monte Carlo simulation and stochastic state-transition approaches. Bai et al. [21] focused on probabilistic reliability evaluation using universal generating function (UGF)-based modeling, Monte Carlo simulation, and performance-sharing mechanisms among wind power regions. Garip et al. [22] investigated microgrid reliability under centralized and decentralized control by analyzing operational coordination, communication structures, and control reliability. Sandelic et al. [23] reviewed microgrid design and planning, including reliability modeling, planning methodologies, and operational considerations for improving resilience. Firouzi et al. [24] evaluated the reliability of integrated power systems with renewable energy using non-sequential Monte Carlo simulation, uncertainty modeling, and probabilistic state analysis.

IRENA reported that the cost of electricity from solar PV and wind has declined, making them competitive in many regions [25]. Battery energy storage costs have also decreased, as reported by NREL and Lazard [26–28]. Hydrogen-based fuel cell technologies can improve microgrid resilience and support operation during periods of low renewable generation [29].

Morais et al. [30] proposed an MILP-based optimal scheduling framework for an isolated renewable microgrid comprising a wind turbine, photovoltaic system, fuel cell, and battery energy storage system. The study showed that MILP-based scheduling can minimize operating costs while satisfying power balance and operational constraints, thereby improving the economics and reliability of the operation of isolated hybrid microgrids.

Lund et al. [31] highlighted that battery energy storage systems and flexible energy management strategies are increasingly important for improving system reliability, operational flexibility, and renewable energy utilization in future smart grids. Recent studies have extensively employed advanced optimization techniques for microgrid energy manage-

ment to achieve economical operation, improved flexibility, and reduced carbon emissions while satisfying system constraints [32–35]. Upadhyay et al. [36] reviewed recent advancements in building-integrated photovoltaic/thermal (BIPVT) systems and reported improved energy efficiency, exergy performance, and long-term economic benefits compared with standalone photovoltaic and thermal systems. The study also emphasized the role of optimization techniques such as GA and PSO in enhancing system performance while promoting sustainable building energy management and smart grid integration. Tiwari and Deo [37] evaluated the design and performance of a virtual grid-connected photovoltaic system for Indian climatic conditions. By analyzing energy generation characteristics, the design demonstrated technical feasibility, and the study provided useful insights for PV system design and optimization in diverse climates. Tiwari et al. [38] investigated the energy performance of the SODHA BERS Complex using passive building design strategies to improve thermal comfort and reduce energy consumption. The study showed that integrating passive architectural features can significantly enhance building energy efficiency and reduce operational energy demand. These advances have motivated the adoption of energy management system (EMS) strategies to optimally dispatch energy resources, improve reliability, and reduce operating costs. Accordingly, this work provides a systematic comparison of three EMS levels for a renewable microgrid under 16 identified failure scenarios.

3. Description of Microgrid System

3.1. Microgrid System Components

The microgrid considered in this work consists of solar PVs, wind generation, a battery, a fuel cell, and a load [26–28,30]. The system is designed to improve the reliability with which load demand can be met through an EMS. The primary renewable energy sources (RESs) are solar PVs and wind. The battery supplies power when renewable generation is insufficient and is charged when surplus power is available after meeting the load demand. The fuel cell operates when renewable generation is insufficient and the battery state of charge (SoC) is below its minimum limit. The component ratings are summarized in Table 1.

Table 1. Microgrid components and their capacity.

Component	Capacity (kW)
Solar PV	2000
Wind Turbine	3000
Battery	300 kW, 1250 Ah–12 V batteries: 20 units connected in series, and five such strings connected in parallel
Fuel Cell	100

3.2. Description of Selected Load Profile

Load demand is a key factor affecting supply reliability and the energy management of RES-based systems. Because demand varies continuously throughout the day, a representative load profile is required to evaluate RES adequacy and to assess the effectiveness of the proposed EMS.

The load dataset used in this study contains hourly electricity demand observations. From this dataset, a 24-h load profile was selected and used throughout this study to assess system reliability under three cases: (i) without EMS, (ii) with EMS, and (iii) with EMS and optimal scheduling. Figure 1 shows the 24-h load, solar, and wind profiles considered in this study.

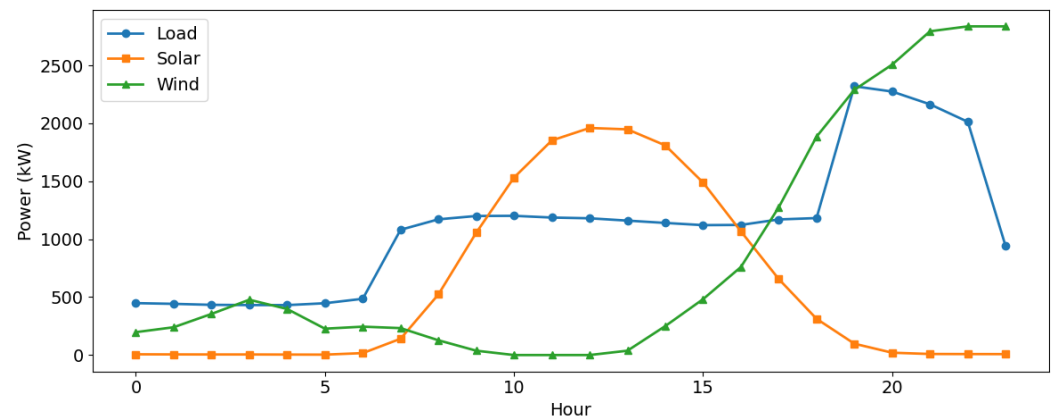


Figure 1. The 24-h load, solar, and wind profiles (12 a.m. to 11 p.m.) [39].

4. Framework of Energy Management System

This section describes the energy management framework used to coordinate the microgrid's energy sources. Three EMS frameworks and their effects on microgrid reliability were investigated: (i) without EMS, (ii) with EMS, and (iii) EMS with optimal scheduling. For each framework, performance was evaluated with the same 24-h load profile, under the same operating scenarios, using common reliability indices.

4.1. Microgrid Without EMS

The operating logic of a microgrid without an EMS is as follows: The power supplied to the load follows a rule-based sequential dispatch strategy (solar PV → wind → battery → fuel cell). When generation is insufficient, the battery discharges; during discharge, SoC limits are not enforced, and the battery is charged only when surplus renewable power is available after meeting the load demand. Figure 2 depicts the microgrid configuration without an EMS adopted in this study.

Rule-Based Energy Dispatch Strategy (Without EMS)

In the no-EMS case, the available energy sources are dispatched using a sequential energy dispatch strategy without forward-looking optimization or SoC-based scheduling [20,22–24]. The dispatch priority is defined as

$$PV \rightarrow Wind \rightarrow Battery \rightarrow FC \quad (1)$$

At each interval t , the renewable power supplied is first computed as

$$P_{RES}(t) = P_{PV}(t) + P_{Wind}(t) \quad (2)$$

The remaining power deficit $D_1(t)$ after renewable utilization is

$$D_1(t) = P_L(t) - P_{RES}(t) \quad (3)$$

where $P_L(t)$ is the load at interval t . The battery discharge is then determined as

$$P_{Battery}^{dis}(t) = \min \left[D_1(t), P_{Battery}^{avail}(t) \right] \quad (4)$$

The residual deficit after battery support is

$$D_2(t) = \left[D_1(t) - P_{Battery}^{dis}(t) \right] \quad (5)$$

The fuel cell output is then

$$P_{FC}(t) = \min[D_2(t), P_{FC}^{max}] \quad (6)$$

Finally, the unmet load (load shedding) is calculated as

$$LS(t) = [D_2(t) - P_{FC}(t)] \quad (7)$$

This formulation represents a rule-based dispatch strategy in which the battery is discharged only when an instantaneous deficit occurs, without considering SoC scheduling or optimization.

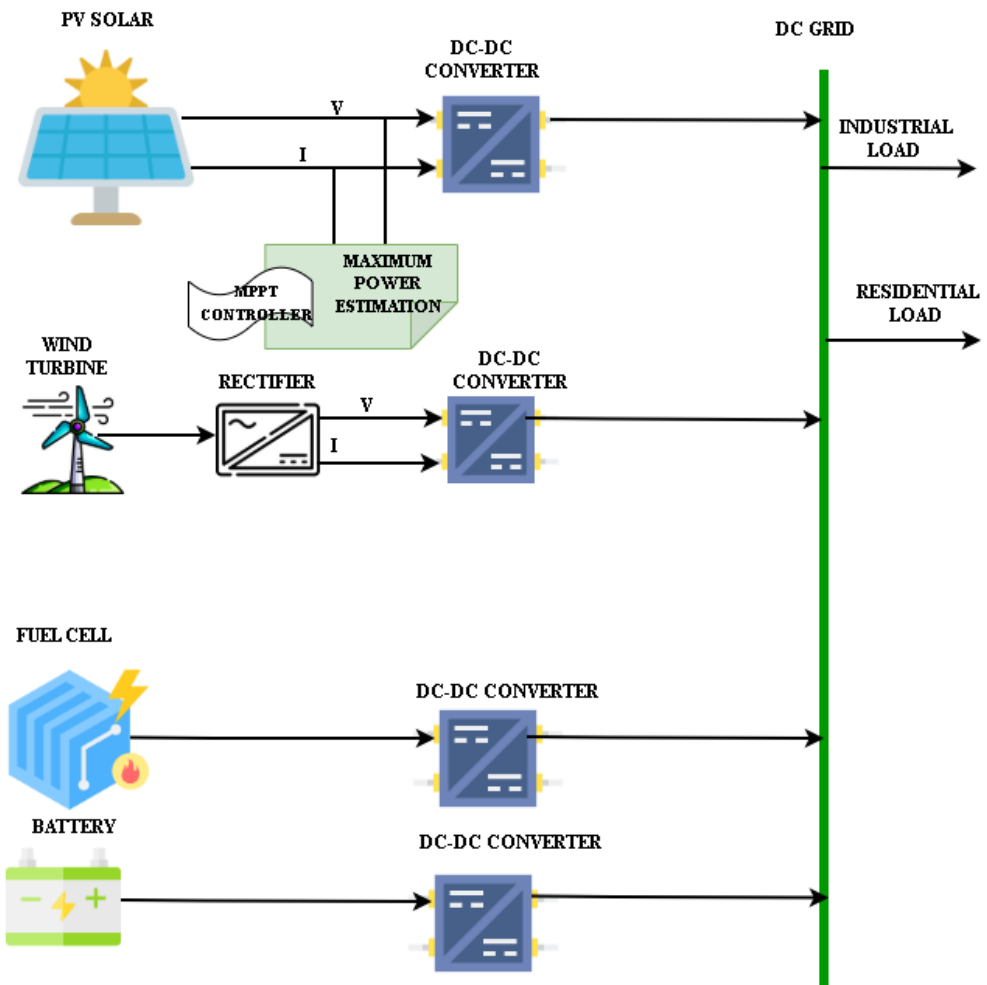


Figure 2. Microgrid without EMS.

4.2. Microgrid with EMS

With an EMS, the microgrid operates using coordinated control of the available resources. Figure 3 shows the microgrid configuration with an EMS.

The purpose of the EMS is to maximize the utilization of renewable generation and reduce the power deficit. Accordingly, the EMS takes as inputs the solar PV power $P_{PV}(t)$, wind power $P_{wind}(t)$, battery power $P_B(t)$, fuel cell power $P_{FC}(t)$, and load demand $P_L(t)$. Based on these inputs, the EMS selects an operating mode to enhance supply reliability.

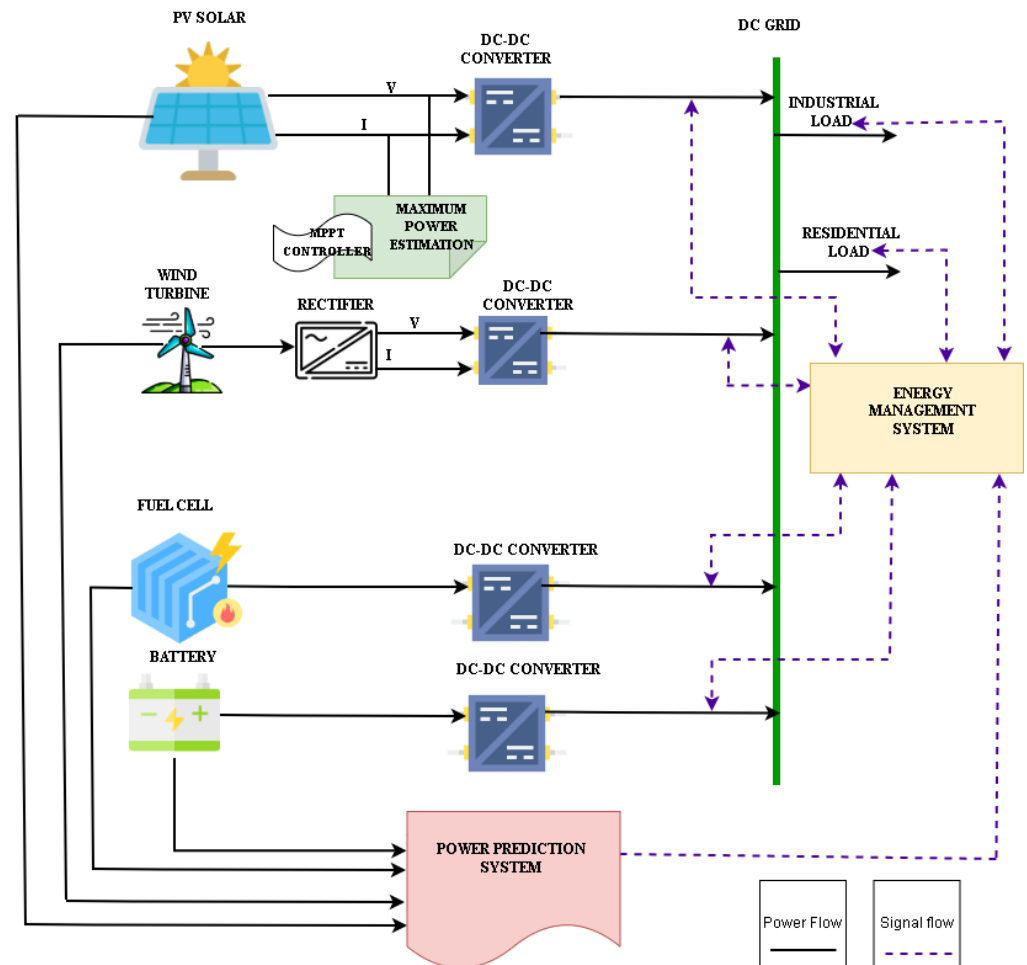


Figure 3. Microgrid with EMS.

EMS Decision Logic for Energy Dispatch

The EMS energy dispatch decision logic used in this study is summarized below. Figure 4 illustrates the proposed EMS flow.

Case 1: Load is less than or equal to generated power.

$$P_{PV}(t) + P_{wind}(t) \geq P_L(t) \quad (8)$$

In this case, the renewable sources supply the load, and surplus power is used to charge the battery if the battery SoC is below SOC_{max} .

Case 2: Load is greater than generated power.

$$P_{PV}(t) + P_{wind}(t) \leq P_L(t) \quad (9)$$

To compensate for the deficit, the EMS discharges the battery (subject to SoC limits). The battery discharge power is

$$P_B(t) = P_L(t) - (P_{PV}(t) + P_{wind}(t)) \quad (10)$$

The battery discharges only when its SoC is above the minimum allowable limit.

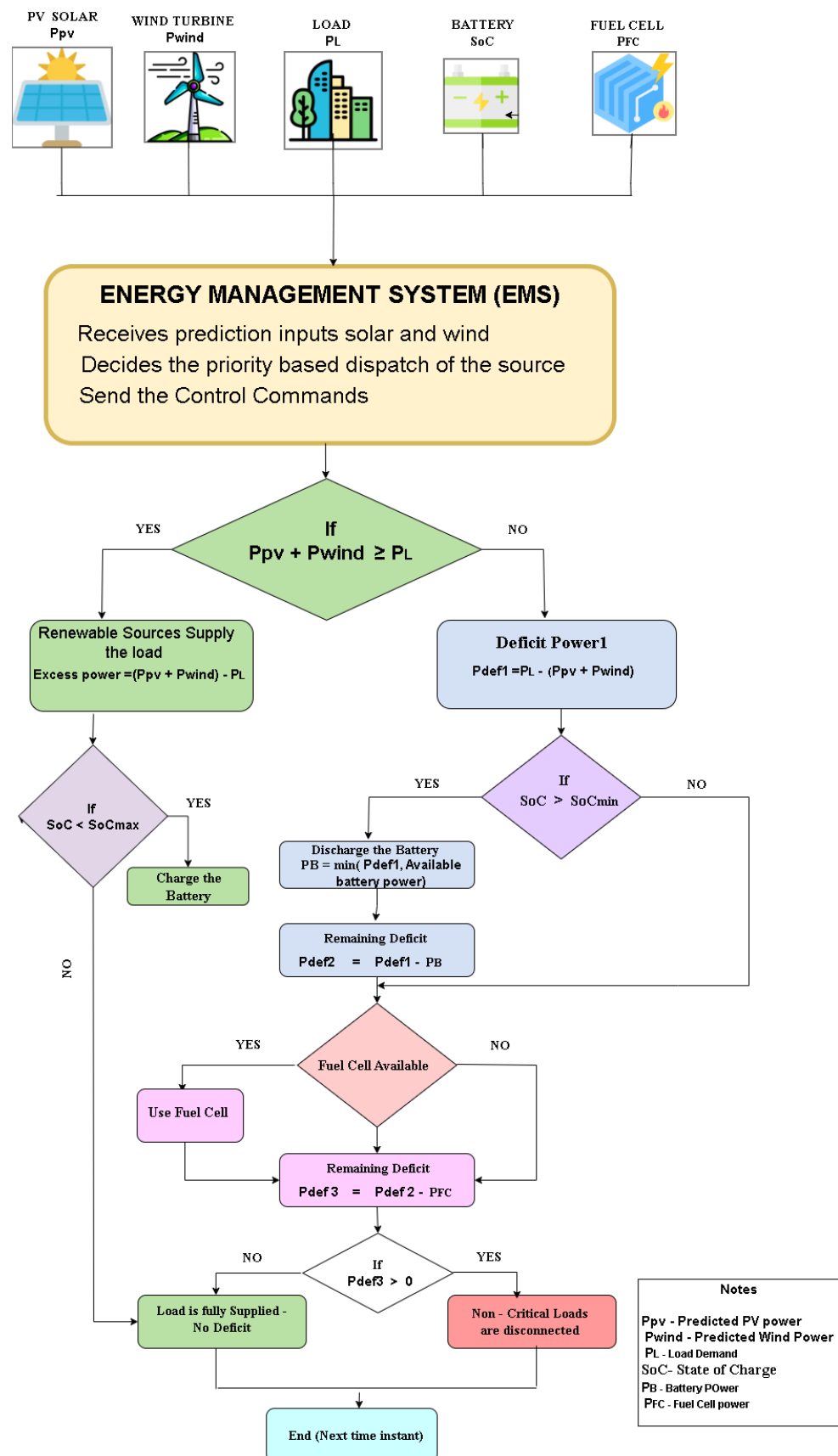


Figure 4. EMS flowchart.

Case 3: Battery SoC is below the minimum limit.

When $SOC(t) \leq SOC_{min}$, the EMS uses the fuel cell to compensate for the deficit.

$$SOC(t) \leq SOC_{min} \quad (11)$$

The fuel cell power output is

$$P_{FC}(t) = P_L(t) - (P_{PV}(t) + P_{wind}(t) + P_B(t)) \quad (12)$$

Case 4: Total supplied power is less than the load demand.

$$P_{PV}(t) + P_{wind}(t) + P_B(t) + P_{FC}(t) < P_L(t) \quad (13)$$

In this case, the EMS serves only the critical loads and disconnects the remaining non-critical loads.

$$P_{shed}(t) = P_L(t) - (P_{PV}(t) + P_{wind}(t) + P_B(t) + P_{FC}(t)) \quad (14)$$

Overall, this energy dispatch strategy prioritizes renewable generation and uses backup sources to compensate for deficits [20,22–24].

4.3. Mixed-Integer Linear Programming-Based Optimized EMS

MILP is mostly used for the optimal scheduling of renewable microgrids, as it optimizes continuous and binary decision variables while satisfying various operational constraints [31,35–37]. The proposed MILP-based EMS framework allocates the optimal power among the resources: PV, wind, battery and fuel cell, by also satisfying the operational constraints over a scheduling horizon. Figure 5 provides a diagrammatic representation of a microgrid with an EMS and optimal scheduling.

The optimization is performed over a 24-h scheduling horizon using the load demand profile and the available solar and wind power profiles. The MILP-based optimized EMS dispatches the available energy efficiently to satisfy the load demand while reducing the overall cost.

4.3.1. Decision Criterion Function

The MILP objective function minimizes the total operating cost while satisfying system constraints:

$$\min Z = \sum_{t=1}^{24} \left[C_{FC} P_{FC}(t) + C_B \left(P_B^{ch}(t) + P_B^{dis}(t) \right) + C_{LS} LS(t) \right] \quad (15)$$

where

- Z : total operating cost;
- $P_{FC}(t)$: fuel cell output (kW);
- $P_B^{ch}(t)$: battery power while charging (kW);
- $P_B^{dis}(t)$: battery power while discharging (kW);
- $LS(t)$: load shedding (kW);
- C_{FC} : fuel cell operating cost coefficient;
- C_B : battery cycling cost coefficient;
- C_{LS} : load-shedding penalty coefficient.

The decision variables used in the proposed MILP optimization model are summarized in Table 2, while the optimization constraints governing the system operation are presented in Table 3. The optimizer prioritizes renewable energy sources because they have marginal

operating costs and then utilizes the battery and fuel cell as needed. As a result, the dispatch schedule reduces operating costs, maintains power balance, and satisfies all operational constraints of the microgrid [31,35–37].

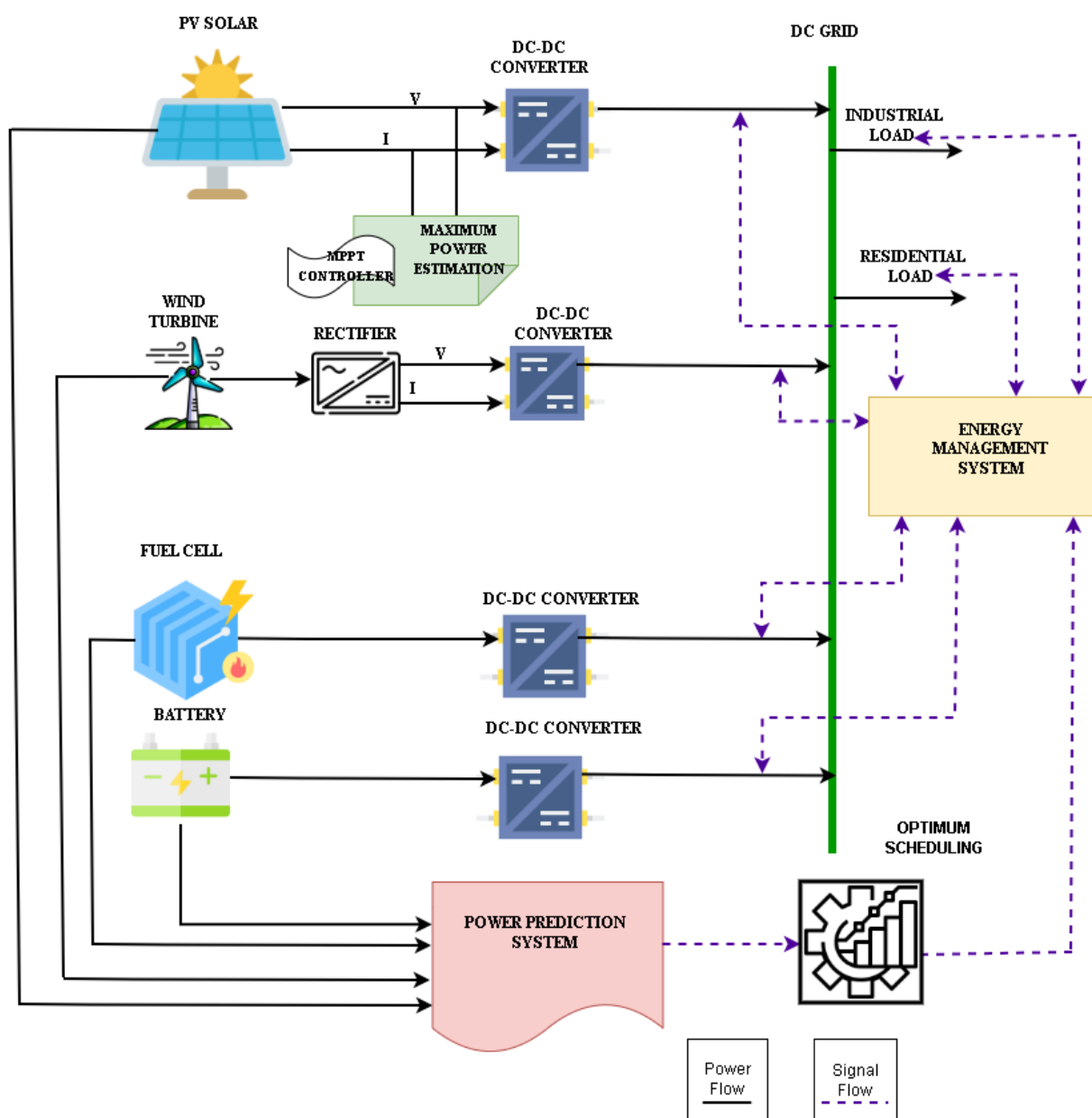


Figure 5. Microgrid with EMS and optimum scheduling.

Table 2. Decision variables used in proposed MILP optimization.

Variable	Description
$P_{PV,t,s}$	Photovoltaic power dispatched (kW)
$P_{wind,t,s}$	Wind power dispatched (kW)
$P_{B,t,s}^{ch}$	Battery power while charging (kW)
$P_{B,t,s}^{dis}$	Battery power discharging (kW)
$SOC_{t,s}$	SoC of battery
$P_{FC,t,s}$	Fuel cell power output (kW)
$LS_{t,s}$	Load shedding (kW)
$u_{t,s}$	Binary charging/discharging decision variable

Table 3. Optimization constraints.

Constraint	Purpose
Power balance	Equality of supply and demand
Battery SOC dynamics	Conservation of energy
SOC limits	Protection of battery
Battery charging limit	Capacity constraint for charging
Battery discharging limit	Capacity constraint for discharging
Fuel-cell limit	Capacity constraint for generator
Load shedding	Unmet demand
Binary constraint	It prevents simultaneous charging and discharging

The optimization stratagem is illustrated in Algorithm 1.

Algorithm 1 MILP-based optimized energy management system

- 1: Input hourly PV generation, wind generation profiles and load demand
 - 2: To initialize battery state of charge (SOC_0)
 - 3: To define battery, fuel cell and renewable generation limits
 - 4: Devise the MILP objective function
 - 5: Implement power balance, renewable generation, battery SOC dynamics and SOC limits, battery charging/discharging, fuel cell operating constraints
 - 6: Solve the MILP using the PuLP optimization library
 - 7: Obtain the optimal hourly dispatch schedule
 - 8: Compute the operating cost of the optimized dispatch
 - 9: Evaluate the optimized dispatch under the sixteen operating scenarios
 - 10: Calculate LOLE, LOLP, EENS and system reliability
 - 11: Report the optimized energy management schedule and reliability indices
-

4.3.2. Computation and Practical Applicability

The optimization problem has continuous power dispatch variables and binary battery variables. This results in a computationally efficient MILP formulation. The optimization model was implemented using the PuLP optimization library in Python 3.12.13 and solved using the CBC solver within the Google Colab environment. The formulation also supports the addition of energy resources or operational constraints in future research.

5. Methodology for Reliability Assessment

The reliability assessment methodology describes the operational availability of microgrid components for meeting load demand under various operating scenarios.

5.1. Reliability Parameters

The reliability characteristics of each component are represented by its mean time to failure (MTTF) and mean time to repair (MTTR), which are used to evaluate component availability and unavailability [5,13].

The MTTF is the average operating duration of a component before a failure occurs, whereas the MTTR is the average time required to restore a failed component to its normal operating condition [5,13].

The forced outage rate (FOR) is the probability that a component is unavailable due to a forced outage [5,13]:

$$FOR = \frac{MTTR}{MTTF + MTTR} \quad (16)$$

The availability factor (TA) is the probability that a component remains operational during the study period [5,13]:

$$TA = \frac{MTTF}{MTTF + MTTR} \quad (17)$$

Since the availability factor and forced outage rate are complementary reliability measures, they satisfy [5]:

$$TA = 1 - FOR \quad (18)$$

The effective availability (EA) of each renewable generation source is determined by its capacity factor (CF) [18,22]:

$$EA = TA \times CF \quad (19)$$

Table 4 summarizes the generation capacity and availability of each microgrid component.

Table 4. Generation capacity and availability of each microgrid component.

Component	Capacity (kW)	TA	FOR (1-TA)
Solar PV	2000	0.995	0.0050
Wind Turbine	3000	0.979	0.0210
Battery	300	0.999	0.0003
Fuel Cell	100	0.999	0.0009

5.2. Microgrid Operating Scenarios

The operating scenarios depend on the availability status of individual microgrid components. In this study, the microgrid operating states were represented by 16 common scenarios.

The microgrid system considered consists of solar PVs, wind, a battery, and a fuel cell supplying a load. Since each component has two possible operating states (available or unavailable), the total number of operating scenarios is [5,13]:

$$N = 2^n \quad (20)$$

where n denotes the number of system components.

For the system considered,

$$N = 2^4 = 16 \quad (21)$$

Hence, sixteen operating scenarios were considered in the reliability assessment.

Table 5 summarizes the sixteen operating scenarios considered in this study. A binary state representation is adopted, where '1' indicates component availability, and '0' represents unavailability.

Table 5. Operating scenarios of microgrid components.

Case	Solar	Wind	Battery	Fuel Cell
1	1	1	1	1
2	0	1	1	1
3	1	0	1	1
4	1	1	0	1
5	1	1	1	0
6	0	0	1	1
7	0	1	0	1
8	0	1	1	0
9	1	0	0	1
10	1	0	1	0

Table 5. *Cont.*

Case	Solar	Wind	Battery	Fuel Cell
11	1	1	0	0
12	0	0	0	1
13	0	0	1	0
14	0	1	0	0
15	1	0	0	0
16	0	0	0	0

5.3. Operating Scenario Probability Calculation

The probability of each operating state is calculated from the availability and unavailability of the sources [5,13].

The probability of occurrence of the j th operating scenario is given by

$$P_{C_j} = \prod_{i=1}^n P_i \quad (22)$$

where P_{C_j} denotes the probability of the occurrence of the j th operating scenario, P_i represents either the availability factor (TA) or the forced outage rate (FOR) of the i th component depending on its operating state, and ' n ' is the count of the components in the microgrid.

For Scenario 1, all resources are available; therefore, the scenario probability is calculated as the product of the availability factors of all four components:

$$P_{C1} = TA_{Solar} \times TA_{Wind} \times TA_{Battery} \times TA_{FC} \quad (23)$$

$$P_{C1} = 0.995 \times 0.979 \times 0.999 \times 0.999 = 0.9719 \quad (24)$$

Similarly, the probabilities of the remaining operating scenarios are obtained.

As observed from Table 6, Scenario 1 has the highest occurrence probability as all components are available. The probabilities of the remaining scenarios decrease as one or more components experience outages. These scenario probabilities are used in the computation of the reliability indices, namely, LOLE, LOLP, EENS, and overall system reliability.

Table 6. Operating scenarios of microgrid components and their probabilities.

Case	Solar	Wind	Battery	Fuel Cell	Probability
1	1	1	1	1	0.9719
2	0	1	1	1	0.00533
3	1	0	1	1	0.02130
4	1	1	0	1	0.00026
5	1	1	1	0	0.00097
6	0	0	1	1	0.00012
7	0	1	0	1	1.42×10^{-6}
8	0	1	1	0	5.33×10^{-6}
9	1	0	0	1	5.68×10^{-6}
10	1	0	1	0	2.13×10^{-5}
11	1	1	0	0	2.59×10^{-7}
12	0	0	0	1	3.11×10^{-8}
13	0	0	1	0	1.17×10^{-7}
14	0	1	0	0	1.42×10^{-9}
15	1	0	0	0	5.68×10^{-9}
16	0	0	0	0	3.11×10^{-11}

5.4. Reliability Indices

The reliability of the microgrid considered in this study was assessed using LOLE, LOLP, EENS, and overall reliability. These indices indicate the capability of the system to serve the load [5,9,13,22].

(i) The LOLE is the expected duration during which the available power is inadequate to satisfy the load [5,9,13].

$$LOLE = \sum_{j=1}^n P_{C_j} \times T_j \quad (25)$$

where P_{C_j} is the probability of occurrence of the j th operating scenario, T_j denotes the duration for which the corresponding scenario causes a loss of load, and n is the total count of operating scenarios.

(ii) The LOLP represents the probability that the available power is unable to satisfy the system load during the study period [5,9,22].

$$LOLP = \frac{LOLE}{T} \quad (26)$$

where T is 24 h in the present work.

(iii) The EENS is the expected amount of energy not supplied as the generated capacity is insufficient [5,13,22].

$$EENS = \sum_{j=1}^n P_{C_j} \times P_{Def,j} \times T_j \quad (27)$$

where $P_{Def,j}$ denotes the power deficit corresponding to the j th operating scenario.

(iv) Reliability (%) is determined from the LOLP and represents the probability that the available power is capable of satisfying the demand of the load throughout the 24 h [5,13,22].

$$Reliability(\%) = (1 - LOLP) \times 100 \quad (28)$$

This study analyzed system reliability under three cases: (i) without EMS, (ii) with EMS, and (iii) with EMS with optimal scheduling.

6. Results and Discussion

The proposed EMS was evaluated by comparing system performance under three configurations:

1. Without EMS;
2. With EMS;
3. With EMS and optimal scheduling.

The comparison was performed using reliability indices including LOLP, LOLE, EENS, and overall reliability.

6.1. Reliability Without EMS

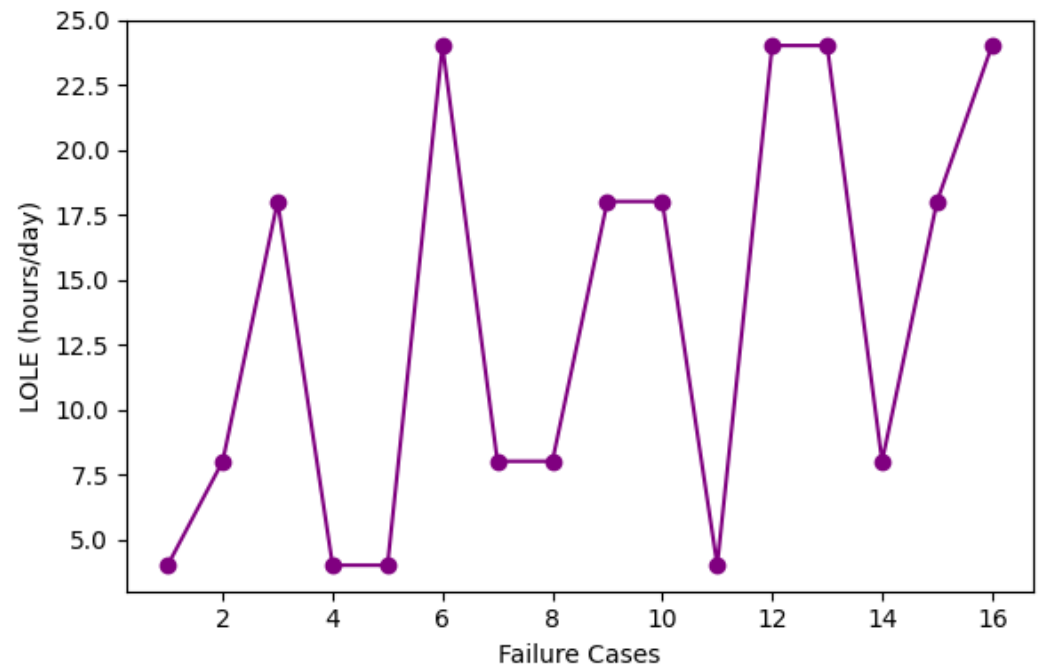
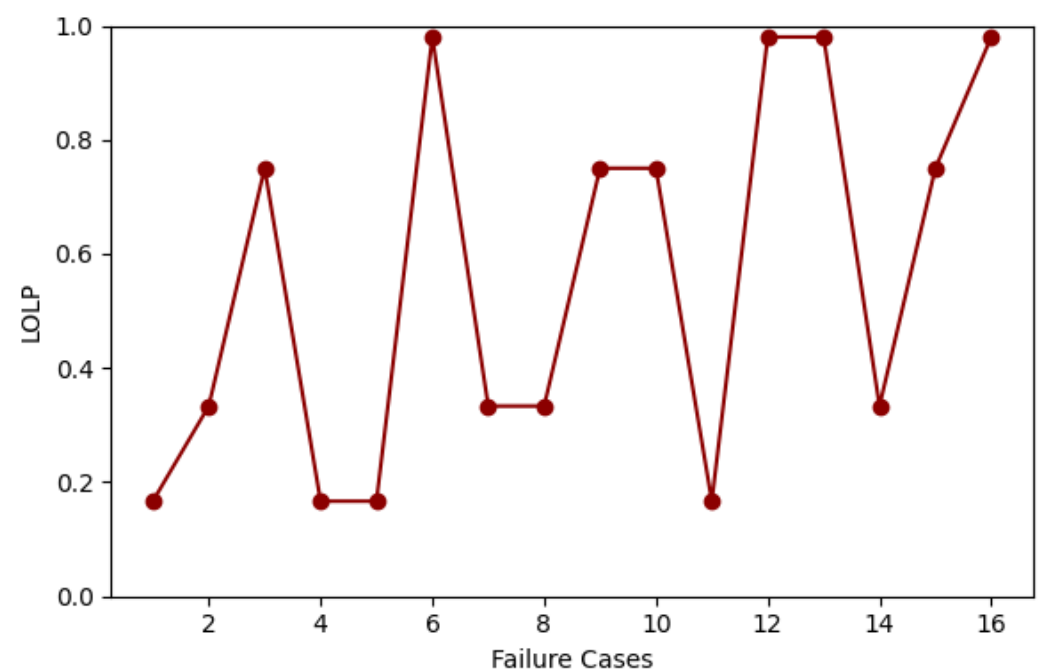
Without an EMS, the reliability indices are higher because the resources are not coordinated or prioritized based on availability. The results are detailed in Table 7 for Case 11.

The reliability indices, LOLE, LOLP, and EENS, for all 16 failure scenarios without the EMS indicated significantly degraded system performance under multiple component outages, with higher outage duration, probability, and expected energy not supplied.

Correspondingly, the reliability decreases sharply in these scenarios, as shown in Figures 6–9, highlighting the system's inability to meet the load demand without coordinated energy management.

Table 7. Results of reliability evaluation without EMS in case 11.

Indices	Meaning	Value	Unit
LOLE	Duration of failure	4	hours
LOLP	Probability of failure	0.166	No unit
EENS	Expected energy not supplied	1245.47	kWh/day
R	Reliability	83.33	%

**Figure 6.** LOLE without EMS.**Figure 7.** LOLP without EMS.

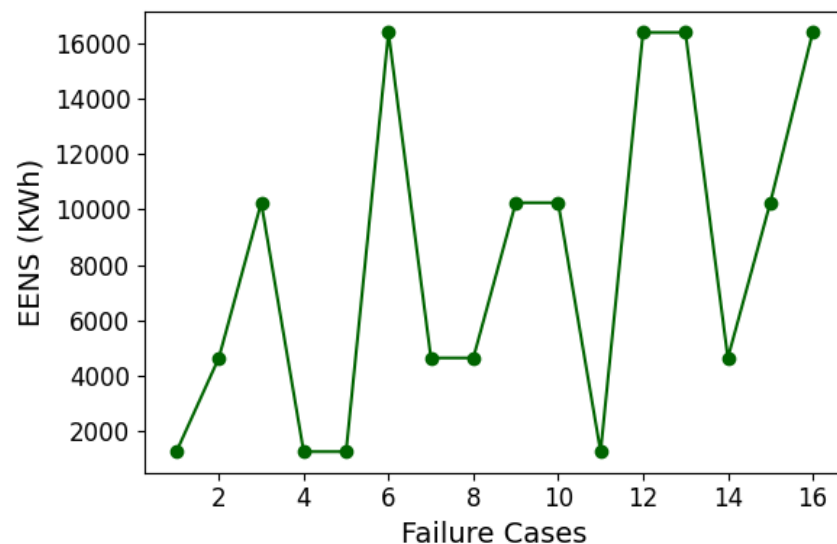


Figure 8. EENS without EMS.

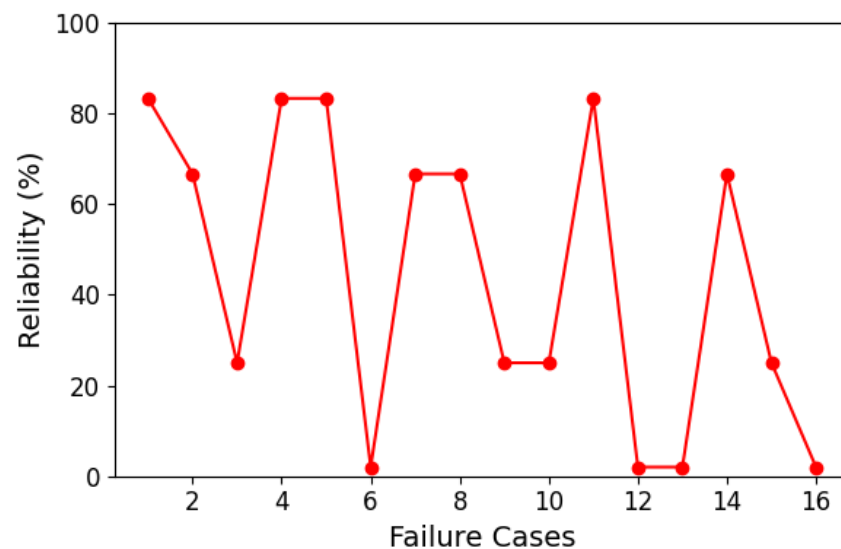


Figure 9. Reliability without EMS.

6.2. Reliability with EMS

With an EMS, the microgrid operates with the coordinated control of the available resources. All available generation sources are integrated with a power prediction system, and the predicted output is provided as the input to the EMS.

Based on the forecast generation and load demand, the EMS allocates the available resources. Renewable sources are utilized as primary generation, while the battery and fuel cell act as backup sources. For each failure scenario, the available generation is determined by the operational status of the components.

Since the EMS has prior information about generation availability, it enables more efficient scheduling and reduces mismatch between supply and demand. This predictive control significantly reduces power deficits compared with operation without an EMS.

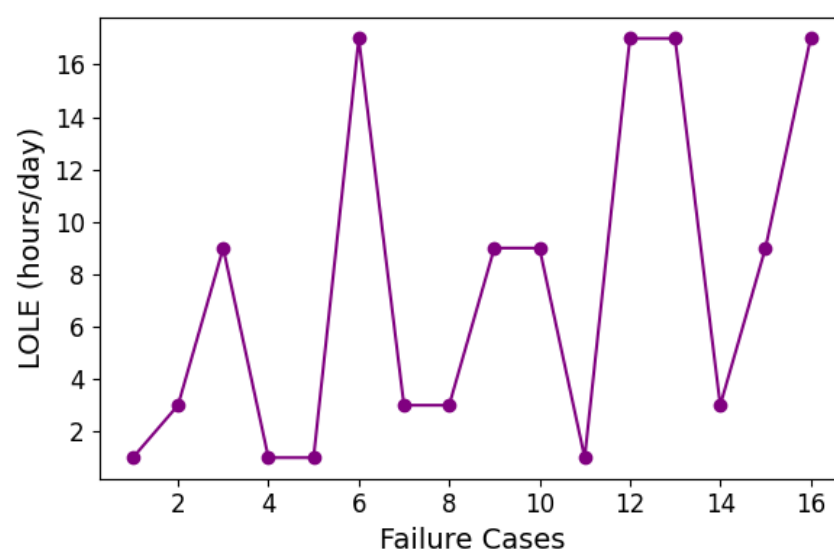
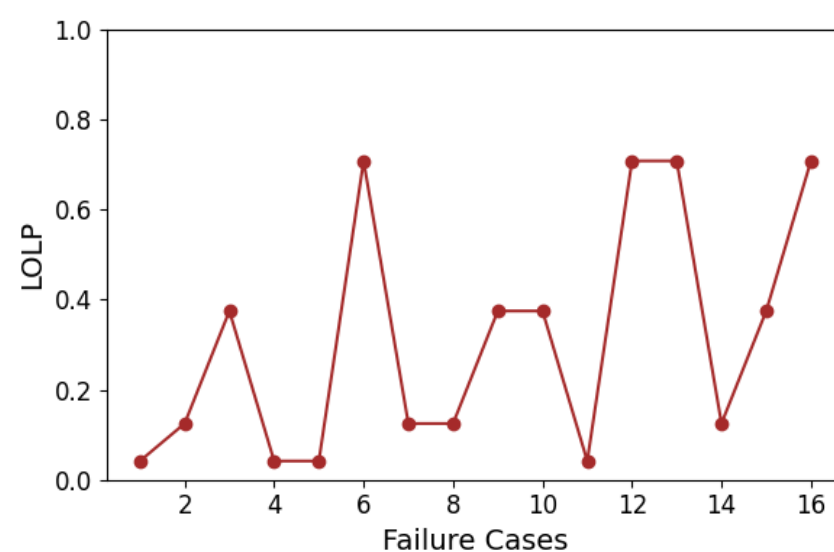
As a result, the reliability indices improve considerably from 83.3% to 95.3%. The reliability evaluation of the system with an EMS is detailed in Table 8 for Case 11.

Table 8. Results of reliability evaluation with EMS in Case 11.

Indices	Meaning	Value	Unit
LOLE	Duration of failure	1	hours
LOLP	Probability of failure	0.04167	No unit
EENS	Expected energy not supplied	200	kWh/day
R	Reliability	95.33	%

With an EMS, the microgrid operates under coordinated control of available resources. The EMS uses predictive strategies to dispatch the battery and fuel cell efficiently to compensate for variability in renewable generation.

The results in Figures 10–13 demonstrate that the implementation of an EMS enables efficient resource utilization, minimizes load interruption, and significantly improves the reliability of the microgrid under 16 scenarios.

**Figure 10.** LOLE with EMS.**Figure 11.** LOLP with EMS.

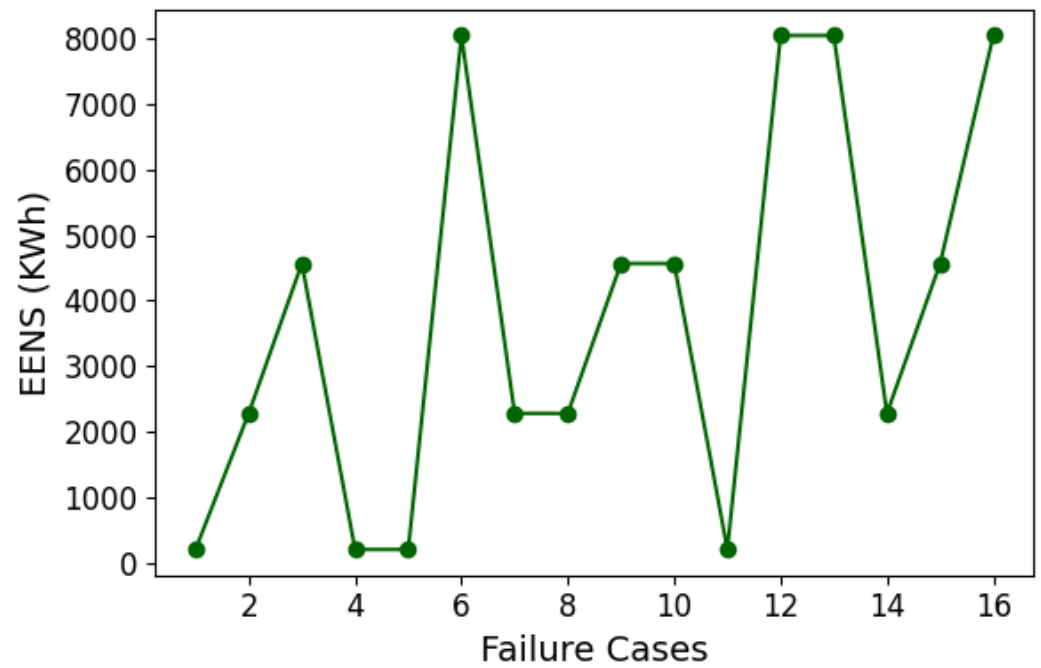


Figure 12. EENS with EMS.

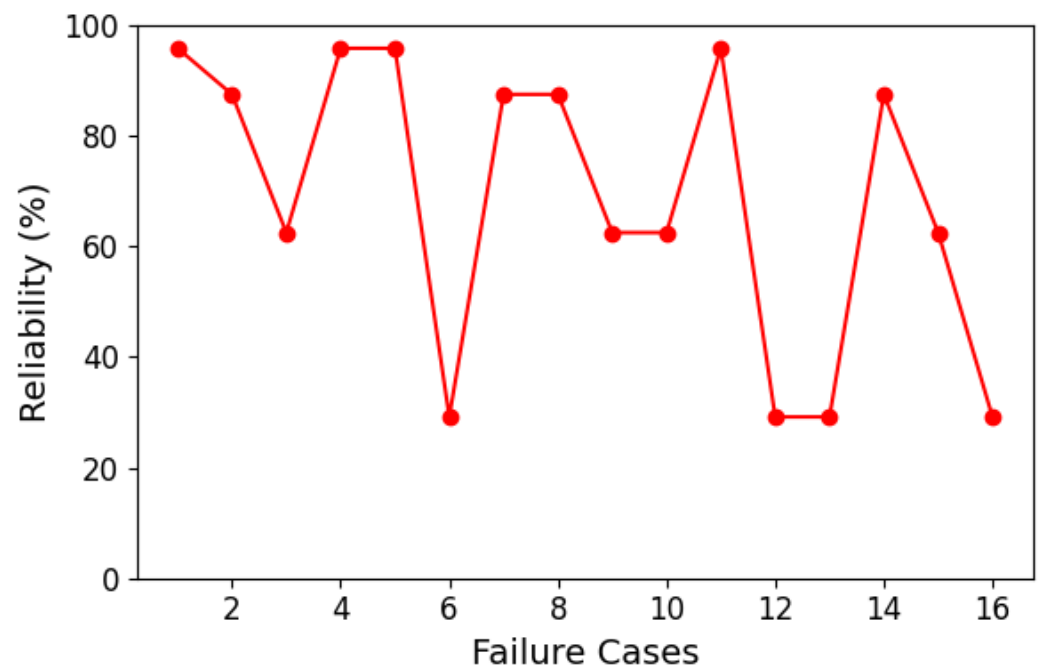


Figure 13. Reliability with EMS.

6.3. Reliability with EMS and Optimum Scheduling

The EMS is enhanced with optimal scheduling based on the cost of energy generation from each source.

The hourly cost comparison between conventional operation and an EMS with optimal scheduling is shown in Figure 14. The results show that the optimized EMS reduces cost across all time intervals. The reduction is more prominent during peak load hours, where optimal scheduling minimizes the use of high-cost fuel cell generation.

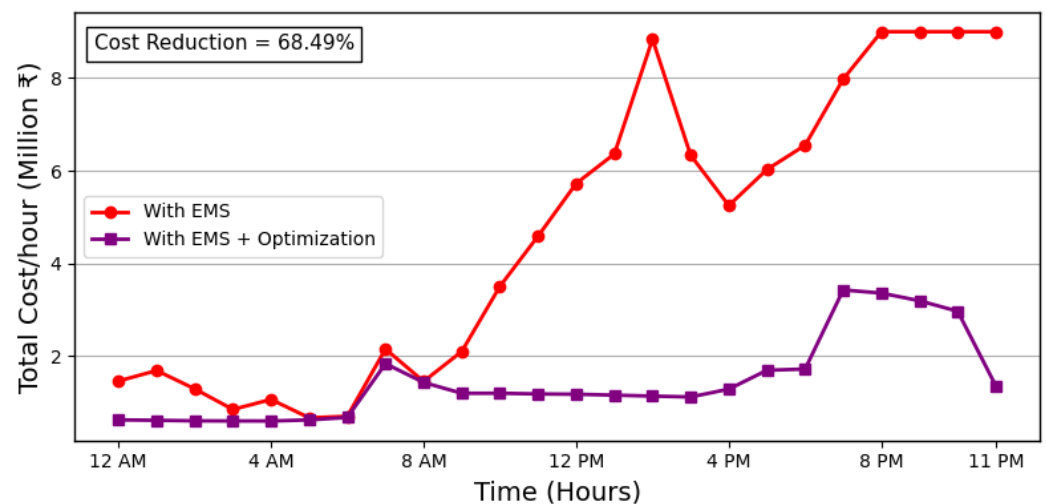


Figure 14. Cost with EMS and optimum scheduling.

The results demonstrate that the proposed EMS with optimal scheduling reduces the total cost by 68.49% per hour.

6.4. Performance Comparison

The performance comparison of the reliability indices in Figure 15 demonstrates the effectiveness of the EMS.

LOLE is significantly reduced with the EMS across all failure scenarios, indicating fewer expected hours of power deficiency. LOLP and EENS are also reduced, implying that the amount of unsupplied energy decreases due to more efficient resource allocation.

Furthermore, microgrid reliability improves considerably with EMS implementation. This enhancement is achieved through improved utilization of available energy sources and effective load management.

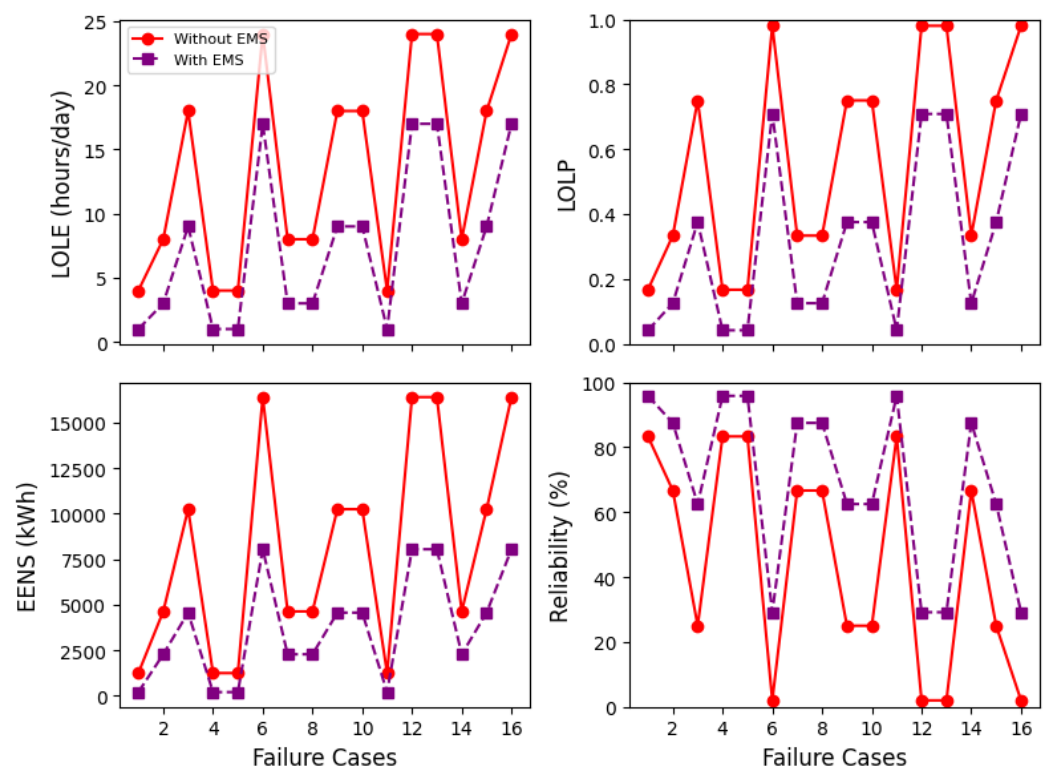


Figure 15. Comparison of reliability indices with and without EMS.

6.5. Comparative Analysis

The reliability indices obtained in this study were compared with the findings reported in the recent literature on renewable-energy-based microgrids and hybrid energy systems. IEEE Std. 1366-2012 and IEEE Std. 762-2006 [40] were adopted as references for the definition and calculation of reliability and availability indices.

Table 9 summarizes the comparison between the proposed framework and selected studies reported in the literature. The comparison includes the system type, reliability indices considered, methodology adopted, and major observations reported by the respective authors.

Table 9. Comparative analysis.

Author's Name	Configuration	Technique	Reliability Assessment for
Nargeszar, A. et al. [20]	PV–wind–battery	Conventional	Renewable resource uncertainty
Garip, S. et al. [22]	Hybrid microgrid	Rule-based control	Reliability of control strategy
Sandelic, M. et al. [23]	PV–wind–battery	Conventional	Storage: improved reliability
Firouzi, M. et al. [24]	Renewable microgrid	Conventional EMS	LOLP, EENS
Proposed	PV–wind–battery Fuel cell	EMS with optimum scheduling	LOLP, LOLE, EENS, and reliability improvement achieved

From the comparison presented in Table 9, it can be observed that the proposed framework incorporates both reliability assessment and energy management functionalities. Unlike several existing studies that primarily focused on reliability evaluation, the proposed approach integrates an energy management system (EMS) with optimal resource scheduling to enhance renewable resource utilization and reduce supply interruptions.

7. Conclusions

The proposed work presents a reliability enhancement framework for renewable-energy-based microgrids using energy management and optimal scheduling. Furthermore, the framework evaluates the practical impact of energy management through comparative reliability analysis using LOLE, LOLP, EENS, and reliability percentage indices under multiple renewable energy failure scenarios. The results demonstrate improved reliability performance and optimized energy scheduling, establishing the proposed framework as a potential solution for next-generation renewable energy microgrids.

This work emphasizes the importance of the integration of EMSs to improve system performance through the coordinated and efficient utilization of available resources. Reliability increases from 83.3% to 95.3%, with substantial reductions in outage duration, probability of failure, and energy not supplied. In addition, optimal scheduling reduces the cost/kWh by up to 68.49%.

Overall, the proposed EMS with optimal scheduling provides an effective solution for enhancing both reliability and economic dispatch in microgrids, supporting real-time implementation in modern power systems.

Future Scope

The scope of this study can be extended by exploring advanced optimization methodologies using industry-oriented software such as MATLAB Optimization Toolbox, CPLEX, Gurobi, and Pyomo.

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