International Journal of Computer Engineering in Research Trends
ISSN: 2349-7084/ https://doi.org/10.22362/ijcert/2025/v12/i05/v12i502
Volume 12, Issue 5, May 2025

Research Paper

AI-Driven Adaptive Energy Management and Fault-Resilient Control Framework for Renewable-Integrated Smart Microgrids with EV Charging Infrastructure

[1*] Korra Cheena

[1*] *Assistant Professor, Department of EEE, University College of Engineering, Kakatiya University, Kothagudem, Bhadradrikothagudem, Telangana, India*

**Corresponding Author(s):* *korrachinna@kakatiya.ac.in*

Received: 06/02/2025 Revised: 17/03/2025 Accepted: 26/05/2025 Published: 31/05/2025

Abstract: The increasing integration of renewable energy sources and electric vehicle (EV) charging infrastructure has improved the sustainability of smart microgrids, but it has also introduced new operational challenges due to renewable power fluctuation, peak EV charging demand, battery constraints, and fault conditions. Conventional energy management methods often fail to coordinate renewable generation, battery storage, grid exchange, and EV charging while maintaining reliable operation during abnormal conditions. To address these limitations, this paper proposes an AI-driven adaptive energy management and fault-resilient control framework for renewable-integrated smart microgrids with EV charging infrastructure. The proposed approach combines AI-assisted short-term forecasting, rule-based battery scheduling, EV charging coordination, and threshold-based fault detection and recovery. A proposed microgrid simulation dataset containing 720 hourly samples over 30 days is used to evaluate solar PV generation, wind generation, load demand, EV charging demand, battery operation, grid exchange, and fault scenarios. The simulation results show that the proposed framework achieves 97.98% renewable energy utilization, 99.08% EV charging satisfaction, and a reduced EV charging delay ratio of 0.92%. It also reduces total energy cost to INR 304,436.02 and lowers grid dependency to 68.36%. Under abnormal conditions, the framework achieves 98.06% fault detection accuracy and 94.80% fault recovery efficiency. These results confirm that the proposed framework provides a simple, adaptive, and reliable solution for improving energy management, EV charging coordination, and fault-resilient operation in renewable-integrated smart microgrids.

Keywords: Smart Microgrid, Renewable Energy Management, Electric Vehicle Charging, Battery Energy Storage, Fault-Resilient Control, AI-Based Energy Management.

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1 Introduction

The rapid growth of renewable energy resources, distributed energy systems, and electric vehicle (EV) charging infrastructure has significantly changed the operation of modern power networks. Smart microgrids have emerged as an effective solution for integrating solar photovoltaic (PV) systems, wind energy, battery energy storage systems, local loads, and utility-grid connections within a controllable energy framework [1], [2]. Unlike conventional centralized power systems, microgrids can operate in both grid-connected and islanded modes, which improves energy reliability, local power management, and renewable energy utilization [3]. This makes microgrids highly suitable for residential communities, institutions, commercial buildings, industrial facilities, and EV charging environments.

Renewable energy integration plays an important role in reducing fossil-fuel dependency and improving the sustainability of power systems [4]. However, solar and wind power generation are naturally intermittent because they depend on weather conditions such as solar irradiance, temperature, and wind speed [5]. This variability creates operational challenges in maintaining the balance between power generation and demand. At the same time, the increasing adoption of EVs introduces additional load demand on microgrids, especially during peak charging periods [6]. Uncontrolled EV charging can increase peak demand, grid dependency, voltage deviation, and energy cost [7]. Therefore, coordinated energy management is required to ensure stable and economical microgrid operation.

Battery energy storage systems are widely used to support renewable-integrated microgrids by storing excess renewable energy and supplying power during low renewable generation or high demand periods [8]. However, improper battery charging and discharging can reduce battery lifetime and affect system reliability. Hence, battery operation must be coordinated with renewable generation, load demand, EV charging demand, and grid power exchange. Artificial intelligence (AI)-based energy management has gained attention because it can support forecasting, decision-making, and adaptive control in dynamic microgrid environments [9].

Although several energy management strategies have been proposed for smart microgrids, many existing methods focus on either renewable energy scheduling, battery management, EV charging control, or fault handling as separate problems [10]. Such independent approaches may not provide effective performance when multiple operating conditions occur together, such as high EV charging demand, low renewable generation, peak load, grid outage, or voltage disturbance. A practical microgrid controller should be able to manage energy flow during normal operation and also respond to abnormal conditions without significantly affecting critical loads and EV charging requirements.

Another important limitation is the complexity of many existing AI-based microgrid control methods. Advanced reinforcement learning, multi-agent control, and optimization-based methods can provide strong performance, but they often require high computational effort, complex tuning, large training datasets, and difficult implementation procedures [11]. For simulation-based academic studies and practical microgrid applications, a simpler and more interpretable framework is often preferred. Such a framework should combine basic AI prediction with transparent control rules so that energy scheduling and fault recovery decisions can be clearly understood and evaluated.

Fault-resilient operation is another major requirement in renewable-integrated microgrids. Faults such as grid outage, voltage sag, overcurrent, low battery state of charge, and EV charger failure can disturb power balance and reduce system reliability [12]. If the controller does not respond quickly, these faults may lead to load curtailment, unstable voltage, poor frequency regulation, and reduced EV charging service. Therefore, a fault-resilient energy management strategy is required to detect abnormal operating conditions and apply corrective actions such as EV charging reduction, battery backup support, load prioritization, and islanded operation [13].

The motivation of this study is to develop a simple, adaptive, and fault-resilient energy management framework for renewable-integrated smart microgrids with EV charging infrastructure. The proposed framework is designed to avoid unnecessary methodological complexity while still addressing the major operational requirements of modern microgrids. Instead of using a fully complex optimization or reinforcement learning model, this study combines AI-assisted forecasting, rule-based battery scheduling, EV charging coordination, and threshold-based fault-resilient control.

The proposed approach uses a microgrid simulation dataset containing hourly data for solar PV generation, wind generation, local load demand, EV charging demand, battery state of charge, grid power exchange, voltage, current, frequency, operating mode, and fault conditions. This dataset allows the proposed framework to be evaluated under normal operation, renewable fluctuation, peak EV demand, and fault-resilient scenarios. The use of a combined simulation-based dataset also supports reproducibility and provides a controlled environment for comparing the proposed method with baseline energy management strategies [14].

The proposed framework aims to improve renewable energy utilization, reduce energy cost, lower grid dependency, and increase EV charging satisfaction, and support stable microgrid operation during abnormal conditions. By treating EV charging as a flexible load and battery storage as a support unit, the controller can adapt energy flow according to renewable availability and system operating conditions. Furthermore, by integrating fault detection and recovery actions into the energy management process, the proposed framework improves the reliability of microgrid operation [15].

The main contributions of this paper are summarized as follows:

1. A simple AI-driven adaptive energy management framework is proposed for renewable-integrated smart microgrids with EV charging infrastructure. The framework combines AI-assisted short-term forecasting with rule-based control to coordinate renewable generation, battery storage, EV charging demand, and grid power exchange.
2. A fault-resilient control strategy is integrated with the energy management process to improve microgrid reliability under abnormal conditions. The proposed strategy uses threshold-based monitoring of voltage, current, frequency, battery state of charge, and grid status to detect faults and apply corrective actions such as EV charging reduction, battery support, load control, and islanded operation.
3. A simulation-based performance evaluation is conducted using the proposed microgrid simulation dataset consisting of 720 hourly samples over 30 days. The proposed method is evaluated using energy cost, renewable energy utilization, grid dependency ratio, EV charging satisfaction, EV delay ratio, battery SOC stability, load curtailment, fault detection accuracy, fault recovery efficiency, voltage deviation, and frequency deviation.

The remainder of this paper is organized as follows. Section II reviews the related work on smart microgrid energy management, renewable integration, EV charging control, and fault-resilient operation. Section III presents the proposed system model, including renewable generation, load demand, battery storage, EV charging, utility grid, power balance, and fault condition models. Section IV describes the proposed methodology, including AI-based forecasting, adaptive energy management, EV charging scheduling, fault detection, fault-resilient control, system architecture, and algorithm. Section V presents the experimental setup, dataset description, simulation scenarios, baseline methods, and performance metrics. Section VI discusses the results and comparative analysis. Finally, Section VII concludes the paper and outlines future research directions.

2 Related Work

The development of renewable-integrated smart microgrids has encouraged extensive research on energy management, battery storage coordination, EV charging control, and fault-resilient operation. Effective microgrid operation requires proper coordination among renewable energy sources, storage systems, flexible loads, utility grid interaction, and protection mechanisms. With the increasing use of EV charging infrastructure, microgrids must also handle additional load demand without affecting system stability. Moreover, fault conditions such as voltage deviation, overcurrent, grid outage, and battery-related issues require fast and reliable control actions. This section reviews the existing studies related to smart microgrid energy management, renewable energy integration, EV charging management, and fault-resilient control, followed by the research gap addressed in this work.

2.1 Energy Management in Smart Microgrids

Energy management in smart microgrids has been widely studied to improve power balance, reduce operating cost, increase renewable energy utilization, and maintain reliable operation. Traditional energy management methods are mainly based on rule-based control, mathematical optimization, model predictive control, and heuristic algorithms. These methods are simple and useful for basic microgrid operation because they use predefined rules or objective functions to decide battery charging, battery discharging, grid import, grid export, and load scheduling [16]. However, their performance may become limited when renewable generation, load demand, electricity price, and EV charging demand change dynamically.

Optimization-based energy management methods have also been used to minimize cost, reduce power losses, and improve energy scheduling in microgrids. Techniques such as linear programming, mixed-integer programming, particle swarm optimization, genetic algorithms, and other metaheuristic methods can provide effective scheduling decisions under specific constraints [17]. However, these methods often require accurate system models and may become computationally expensive when the number of components, operating constraints, and time intervals increases.

In recent years, artificial intelligence-based energy management has gained attention because AI models can learn operating patterns from data and support adaptive decision-making. Machine learning and deep learning models have been applied for load forecasting, renewable power prediction, electricity price forecasting, and energy scheduling [18]. Reinforcement learning-based methods have also been explored for dynamic microgrid control because they can learn control actions through interaction with the operating environment [19]. Despite their advantages, many advanced AI methods are difficult to implement due to high computational complexity, training requirements, and limited interpretability. Therefore, a simple AI-assisted energy management strategy is still required for practical and simulation-based microgrid studies.

2.2 Renewable Energy Integration in Microgrids

Renewable energy integration is a major objective of modern microgrids because it reduces fossil-fuel dependency and supports clean energy operation. Solar photovoltaic and wind energy systems are commonly used as distributed renewable energy sources in microgrids. However, their power output is intermittent and depends on environmental conditions such as solar irradiance, temperature, and wind speed [20]. This variability creates uncertainty in microgrid operation and makes energy balancing more challenging.

To address renewable variability, battery energy storage systems are widely integrated with PV and wind systems. Battery storage absorbs surplus renewable power when generation is higher than demand and supplies stored energy when renewable generation is low or demand is high [21]. Coordinated operation of PV, wind, and battery storage improves renewable energy utilization and reduces unnecessary grid import. It also supports stable operation during peak load and grid disturbance conditions.

Several studies have focused on hybrid renewable microgrids that combine PV, wind, and battery storage for energy management. These studies show that coordinated renewable generation and storage control can improve power quality, reduce operating cost, and enhance system reliability [22]. However, renewable energy integration becomes more complex when EV charging infrastructure is added to the microgrid. EV charging demand may occur during low renewable generation periods, which increases grid dependency and affects voltage stability. Hence, renewable energy management must be coordinated with battery operation and EV charging demand.

2.3 EV Charging Management

The rapid growth of electric vehicles has introduced new challenges for smart microgrid operation. EV charging stations increase the total electricity demand and may create peak load stress if charging is not properly controlled [23]. Uncontrolled EV charging can increase transformer loading, voltage deviation, grid import, and operating cost. Therefore, EV charging management is an important part of microgrid energy management.

Controlled EV charging methods schedule charging based on user requirements, electricity price, renewable availability, grid condition, and battery storage status. In microgrid environments, EV charging can be treated as a flexible load because charging can be shifted or reduced without immediately affecting critical power supply [24]. This flexibility allows the microgrid controller to prioritize EV charging during high renewable generation and reduce charging during peak demand or fault conditions.

Recent EV charging studies have considered renewable-based charging stations, battery-assisted charging, and grid-interactive EV charging systems. These approaches help reduce grid stress and improve the use of locally generated renewable energy [25]. However, many existing studies focus mainly on charging cost reduction or charging demand scheduling. Fault conditions, islanded operation, and load prioritization are often not fully integrated into EV charging management. As a result, EV charging coordination must be combined with fault-resilient control to ensure reliable microgrid operation.

2.4 Fault Detection and Resilient Control

Fault detection and resilient control are essential for maintaining reliable microgrid operation. Microgrids are exposed to different abnormal conditions, including grid outage, voltage sag, overcurrent, frequency deviation, battery fault, renewable generation failure, and EV charger fault. These faults can disturb power balance, reduce power quality, and affect the supply of critical loads [26]. Therefore, microgrid controllers must detect abnormal conditions and apply corrective actions in a timely manner.

Traditional fault detection methods are generally based on threshold monitoring of voltage, current, frequency, and power flow. These methods are simple, fast, and easy to implement because they compare measured values with predefined operating limits [27]. Although threshold-based methods may not provide detailed fault classification, they are useful for practical fault detection in simple simulation-based microgrid studies. They also provide clear decision logic for activating protection and recovery actions.

More advanced studies have used machine learning, deep learning, observer-based control, and fault-tolerant control methods for microgrid protection and recovery. These methods can improve fault classification and support robust control under uncertain operating conditions [28]. However, advanced fault diagnosis models usually require large labeled fault datasets and high computational effort. For a simple and interpretable framework, threshold-based fault detection combined with rule-based recovery actions can provide a practical solution. Corrective actions such as reducing EV charging, disconnecting non-critical loads, using battery backup, and switching to islanded operation can improve fault resilience without making the control system overly complex.

2.5 Research Gap

From the reviewed literature, it can be observed that many existing studies address microgrid energy management, renewable integration, EV charging control, and fault-resilient operation as separate research problems. Energy management studies mainly focus on cost reduction and power scheduling, while renewable integration studies focus on PV, wind, and storage coordination. Similarly, EV charging studies often emphasize charging demand control, and fault detection studies mainly focus on protection or fault classification [29]. This separation limits the ability of existing methods to handle realistic microgrid conditions where renewable fluctuation, EV charging demand, battery constraints, and faults may occur together.

Another important gap is that many AI-based methods are complex and difficult to interpret. Although advanced optimization and reinforcement learning methods can improve microgrid performance, they may not be suitable for simple implementation, small datasets, or transparent academic validation [30]. Therefore, there is a need for a simple integrated framework that combines AI-assisted forecasting, rule-based battery scheduling, flexible EV charging management, and threshold-based fault-resilient control.

To address these gaps, this paper proposes a simple AI-driven adaptive energy management and fault-resilient control framework for renewable-integrated smart microgrids with EV charging infrastructure. The proposed framework uses the proposed microgrid simulation dataset to evaluate renewable utilization, grid dependency, EV charging satisfaction, battery operation, load curtailment, voltage stability, frequency stability, fault detection, and recovery performance.

3 Proposed System Model

The proposed system considers a renewable-integrated smart microgrid with EV charging infrastructure. The microgrid consists of solar photovoltaic generation, wind power generation, battery energy storage system, local loads, EV charging stations, and a utility grid connection. The system is designed to operate under normal grid-connected conditions as well as islanded and fault-resilient conditions. The main purpose of the system model is to describe how energy is generated, stored, supplied, and controlled among different microgrid components.

3.1 Microgrid Architecture

The proposed microgrid includes renewable energy sources, battery storage, EV charging infrastructure, local loads, and utility grid support. Solar PV and wind generation act as the primary energy sources. Since their output varies with solar irradiance, temperature, and wind speed, the battery energy storage system is used to balance power generation and demand.

The battery stores excess renewable energy when generation is higher than demand and supplies power when renewable generation is low or load demand is high. The EV charging station is treated as a flexible load because charging can be adjusted based on renewable availability, battery state of charge, grid condition, and user charging requirements. The utility grid acts as a backup source and supports the microgrid when local generation and battery power are not sufficient.

3.2 Renewable Generation and Load Demand

The renewable generation in the proposed system is obtained from solar PV and wind power units. The combined renewable power is used to supply local loads, charge EVs, charge the battery, or export excess energy to the grid. The total demand of the microgrid consists of regular local load demand and EV charging demand.

The EV charging demand changes according to the number of connected vehicles, arrival time, departure time, initial battery state of charge, and required charging level. Therefore, EV charging is considered controllable and can be reduced or delayed during peak load or fault conditions.

3.3 Battery Energy Storage System

The battery energy storage system is used to improve the reliability and stability of the microgrid. It operates within predefined minimum and maximum state-of-charge limits to avoid deep discharging and overcharging. During surplus renewable generation, the battery is charged. During low renewable generation, high demand, or grid outage, the battery is discharged to support critical loads and reduce grid dependency.

3.4 Utility Grid Interaction

The utility grid is connected to the microgrid through the point of common coupling. During normal operation, the microgrid imports power from the grid when local renewable generation and battery power are insufficient. When renewable generation exceeds demand and the battery is sufficiently charged, excess power can be exported to the grid if allowed. During grid outage or abnormal grid conditions, the microgrid disconnects from the utility grid and operates in islanded mode.

3.5 Fault Conditions and Operating Modes

The proposed system considers simple fault conditions such as grid outage, voltage deviation, overcurrent, low battery state of charge, renewable generation failure, and EV charger fault. These conditions are detected by monitoring voltage, current, frequency, battery SOC, and grid status.

The microgrid operates in three main modes. In grid-connected mode, renewable generation, battery storage, and grid power jointly supply the demand. In islanded mode, the microgrid supplies the load using available renewable power and battery storage without grid support. In fault-resilient mode, the controller applies corrective actions such as reducing EV charging, disconnecting non-critical loads, using battery backup, and prioritizing critical loads.

3.6 Role of the Energy Management Controller

The energy management controller is the central decision-making unit of the proposed system. It receives information from renewable sources, battery storage, EV chargers, local loads, grid connection, and electrical sensors. Based on this information, it decides battery charging/discharging, EV charging scheduling, grid import/export, load control, and fault-resilient actions.

Thus, the proposed system model provides a simple and practical foundation for developing the AI-driven adaptive energy management and fault-resilient control framework for renewable-integrated smart microgrids with EV charging infrastructure.

4 Proposed Methodology

This section presents the proposed AI-driven adaptive energy management and fault-resilient control methodology for a renewable-integrated smart microgrid with EV charging infrastructure. The methodology is designed to be simple, practical, and easy to implement. Instead of using a complex multi-agent or reinforcement learning framework, the proposed approach combines AI-based short-term prediction, rule-assisted energy management, EV charging scheduling, and threshold-based fault-resilient control. The proposed microgrid simulation dataset is used to evaluate the behavior of renewable generation, load demand, EV charging demand, battery operation, grid power exchange, and fault conditions.

4.1 Overview of the Proposed Methodology

The proposed methodology consists of four major stages. First, the input data are collected from the proposed microgrid simulation dataset, which includes renewable generation, load demand, EV charging demand, battery state of charge, grid power, voltage, current, frequency, and fault status. Second, an AI-based forecasting model is used to estimate future renewable generation and load demand. Third, the energy management controller determines the charging and discharging operation of the battery, EV charging schedule, and grid power exchange. Finally, the fault-resilient control unit monitors abnormal conditions and applies suitable corrective actions when a fault is detected.

The main objective of the proposed methodology is to maintain power balance, improve renewable energy utilization, reduce dependency on the utility grid, support EV charging requirements, and ensure reliable microgrid operation during fault conditions.

4.2 Input Dataset and Preprocessing

The proposed methodology uses the proposed microgrid simulation dataset as the input data source. The dataset contains 720 hourly samples representing 30 days of microgrid operation. It includes solar irradiance, PV power, temperature, wind speed, wind power, local load demand, EVs connected, EV demand, EV served power, battery SOC, battery charging/discharging power, grid import/export power, electricity price, voltage, current, frequency, operating mode, fault flag, fault type, curtailed load, and renewable utilization.

Before applying the proposed control strategy, the input data are preprocessed to remove inconsistencies and scale the variables into a common range. The normalized input feature vector at time ttt is represented as:

$$X(t) = \{P_{PV}(t), P_{WT}(t), P_L(t), P_{EV}(t), SOC_B(t), P_{\text{Grid}}(t), V(t), I(t), f(t)\} \quad (1)$$

where $P_{PV}(t)$ and $P_{WT}(t)$ represent PV and wind power, $P_L(t)$ represents local load, $P_{EV}(t)$ represents EV demand, $SOC_B(t)$ represents battery state of charge, $P_{\text{Grid}}(t)$ represents grid power, and $V(t), I(t)$, and $f(t)$ represent voltage, current, and frequency, respectively.

The selected features are used by the forecasting model and the energy management controller to determine the operating condition of the microgrid.

4.3 System Architecture Diagram

The system architecture of the proposed framework shows the interaction among renewable generation, battery storage, EV charging infrastructure, utility grid, local loads, and the central energy management controller. The architecture is divided into three layers: the input layer, decision layer, and control layer.

The input layer receives data from PV generation, wind generation, battery storage, EV charging stations, local loads, utility grid, and electrical measurements. The decision layer contains the AI-based forecasting model and the adaptive energy management controller. The control layer performs battery scheduling, EV charging control, grid power exchange, load adjustment, and fault-resilient recovery actions.

The system architecture diagram can be represented in the paper as Fig. 1.

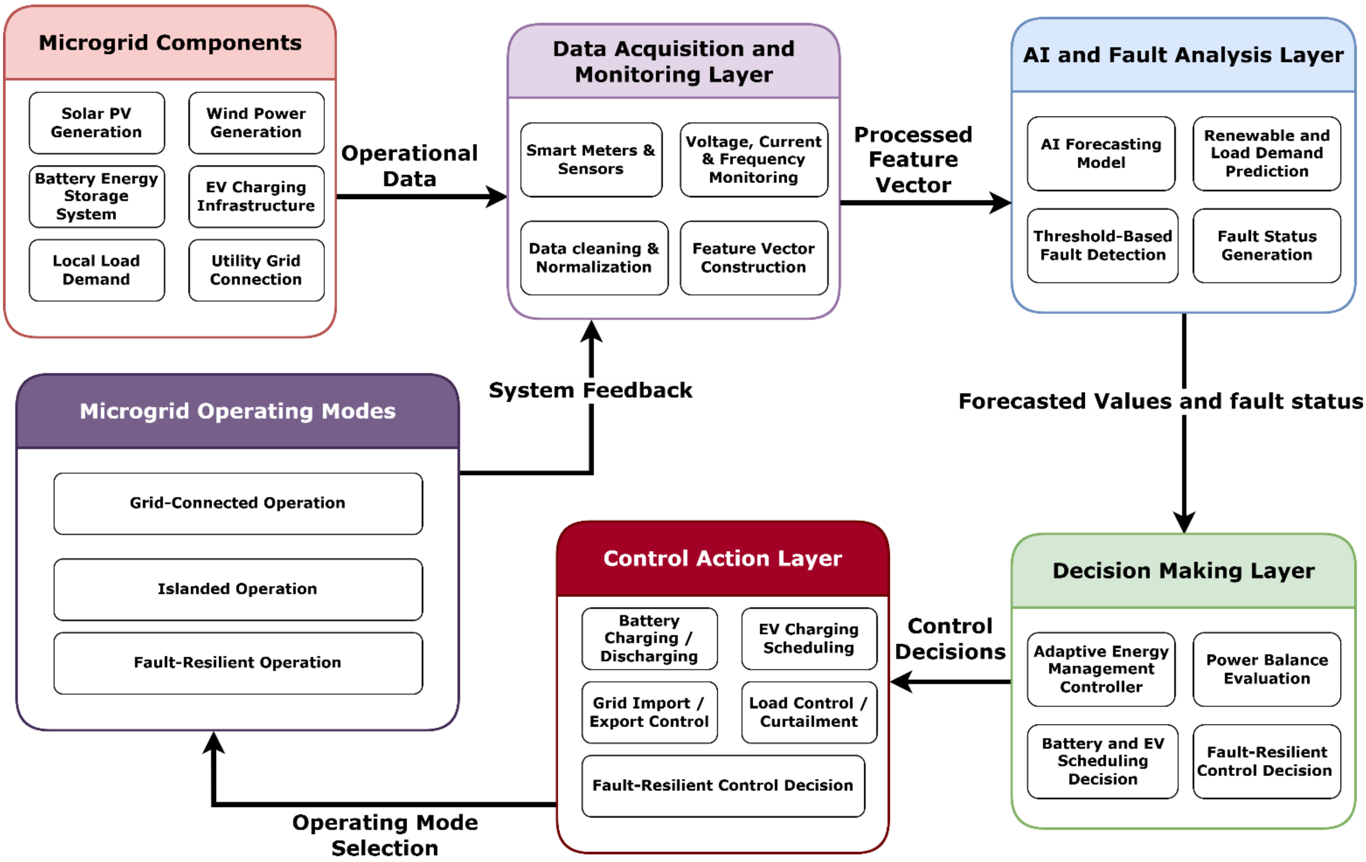

Fig. 1. Proposed AI-driven adaptive energy management and fault-resilient control framework for renewable-integrated smart microgrid with EV charging infrastructure

This architecture clearly shows that the proposed framework does not treat energy management and fault handling as separate tasks. Instead, both are handled through a common controller that receives real-time operating data and generates suitable control decisions.

4.4 *AI-Based Forecasting Module*

The AI-based forecasting module is used to predict short-term renewable generation and load demand. The purpose of forecasting is to help the controller make proactive energy management decisions instead of reacting only to present values. In this study, a simple LSTM or ANN-based forecasting model can be used because the dataset is time-series based and contains hourly microgrid data.

$$\left[\hat{P}_{RES}(t+1), \hat{P}_D(t+1)\right] = F_\theta(X(t)) \tag{2}$$

where $\hat{P}_{RES}(t+1)$ is the predicted renewable power, $\hat{P}_D(t+1)$ is the predicted total demand, F_θ is the trained AI forecasting model, and $X(t)$ is the input feature vector.

The predicted renewable power is calculated using PV and wind generation, while the predicted demand includes local load and EV charging demand. These predicted values are passed to the energy management controller for battery scheduling, EV charging decisions, and grid power exchange.

4.5 *Adaptive Energy Management Strategy*

The adaptive energy management strategy determines how the available energy should be distributed among local loads, EV charging stations, battery storage, and the utility grid. The controller first checks the available renewable power and compares it with the total demand. The power surplus or deficit at time t is calculated as:

$$\Delta P(t) = P_{RES}(t) - P_D(t) \tag{3}$$

where $P_{\mathrm{RES}}(t)$ is the total renewable power and $P_D(t)$ is the total demand.

If $\Delta P(t) > 0$, renewable generation is higher than demand. In this condition, the excess power is used to charge the battery, serve EV charging demand, or export power to the grid. If $\Delta P(t) < 0$, renewable generation is insufficient. In this condition, the controller discharges the battery or imports power from the utility grid. If the grid is unavailable, non-critical loads and low-priority EV charging are reduced.

The battery control action is defined using a simple rule-based decision:

$$P_B(t) = \begin{cases} P_{ch}(t), & \Delta P(t) > 0 \text{ and } SOC_B(t) < SOC_B^{\max} \\ -P_{dis}(t), & \Delta P(t) < 0 \text{ and } SOC_B(t) > SOC_B^{\min} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where $P_B(t)$ is the battery power, $P_{ch}(t)$ is the charging power, $P_{\mathrm{dis}}(t)$ is the discharging power, $SOC_B^{\max}$ is the maximum battery SOC, and $SOC_B^{\min}$ is the minimum battery SOC. In this equation, battery charging is considered positive and battery discharging is considered negative for control decision representation.

4.6 *EV Charging Scheduling Strategy*

The EV charging station is treated as a flexible load in the proposed methodology. The controller schedules EV charging based on renewable power availability, battery SOC, total load demand, and fault condition. EV charging is prioritized during high renewable generation and low local load demand. During peak demand or fault conditions, EV charging is reduced or delayed to maintain system stability.

The EV charging decision is expressed as:

$$P_{EV}^{sch}(t) = \begin{cases} P_{EV}^{\mathrm{req}}(t), & P_{RES}(t) > P_L(t) \text{ and } F(t) = 0 \\ \alpha P_{EV}^{\mathrm{req}}(t), & P_{RES}(t) < P_D(t) \text{ and } F(t) = 0 \\ 0, & F(t) = 1 \text{ and EV priority is low} \end{cases} \tag{5}$$

where $P_{EV}^{sch}(t)$ is the scheduled EV charging power, $P_{EV}^{req}(t)$ is the required EV charging power, $F(t)$ is the fault status, and α is a reduction factor between 0 and 1 .

This strategy ensures that EV charging does not create additional stress during peak demand or fault conditions. High-priority EVs can still be served when enough power is available, while low-priority EV charging can be delayed.

4.7 Fault Detection Strategy

The proposed methodology uses a simple threshold-based fault detection strategy. This approach is selected to keep the framework easy to implement and understandable. The controller continuously monitors voltage, current, frequency, battery SOC, and grid availability. A fault is detected when any monitored parameter exceeds its allowable operating limit.

The fault status is defined as:

$$F(t) = \begin{cases} 1, & V(t) < V_{\min} \text{ or } V(t) > V_{\max} \\ 1, & I(t) > I_{\max} \\ 1, & f(t) < f_{\min} \text{ or } f(t) > f_{\max} \\ 1, & SOC_B(t) < SOC_B^{\min} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where $F(t) = 1$ indicates a fault condition and $F(t) = 0$ indicates normal operation. The monitored faults include voltage deviation, overcurrent, frequency deviation, low battery SOC, grid outage, and EV charger fault.

The fault detection strategy is simple, but it is suitable for the proposed study because the main focus is on adaptive energy management and fault-resilient control rather than complex fault classification.

4.8 Fault-Resilient Control Strategy

Once a fault is detected, the fault-resilient control strategy is activated. The main purpose of this strategy is to maintain power supply to critical loads, protect the battery, reduce system stress, and restore normal operation as early as possible.

The proposed fault-resilient control strategy follows five main actions.

First, the controller identifies whether the fault is related to voltage deviation, overcurrent, grid outage, battery SOC, or EV charging. Second, the controller reduces or disconnects non-critical loads if the available power is not sufficient. Third, low-priority EV charging is delayed to prevent additional load stress. Fourth, the battery is used as backup support if its SOC is within the safe operating range. Finally, if the utility grid is unavailable, the microgrid is switched to islanded mode.

During fault-resilient operation, critical loads are given the highest priority. EV charging is treated as a flexible demand and can be reduced when system stability is affected. This makes the microgrid more reliable during abnormal operating conditions.

4.9 Control Objective

The overall objective of the proposed methodology is to reduce operating cost, improve renewable energy utilization, satisfy EV charging demand, and maintain reliable operation during faults. The control objective is defined as:

$$\min J = \sum_{t=1}^{T} \left(C_{\text{grid}}(t) + C_{\text{curt}}(t) + C_{\text{EVdelay}}(t) + C_{\text{fault}}(t)\right) \tag{7}$$

where J is the total operating objective, $C_{\text{grid}}(t)$ is the grid energy cost, $C_{\text{curt}}(t)$ is the renewable curtailment cost, $C_{\text{EV delay}}(t)$ is the EV charging delay cost, and $C_{\text{fault}}(t)$ is the fault-related penalty.

This objective guides the proposed controller to use renewable energy efficiently, reduce unnecessary grid import, avoid excessive EV charging delay, and improve fault-resilient operation.

4.10 Proposed Algorithm

The proposed algorithm explains the step-by-step operation of the AI-driven adaptive energy management and fault-resilient control framework. It combines forecasting, energy scheduling, EV charging control, and fault-resilient recovery in a single operational sequence. This algorithm can be included in the paper after the methodology explanation to clearly show the working logic of the proposed system.

Algorithm 1: AI-Driven Adaptive Energy Management and Fault-Resilient Control

Input: Proposed microgrid simulation dataset, PV power, wind power, load demand, EV demand, battery SOC, grid power, voltage, current, frequency, and fault status.

Output: Battery control action, EV charging schedule, grid power exchange, load control decision, and faultresilient action.

1. Start the microgrid energy management process.
2. Read hourly input data from the proposed microgrid simulation dataset.
3. Preprocess the input variables and construct the feature vector $X(t)$.
4. Predict renewable generation and total demand using the AI forecasting model.
5. Calculate total renewable power $P_{RES}(t)$.
6. Calculate total demand $P_D(t)$.
7. Compute the power difference $\Delta P(t)$.
8. Check battery SOC limits.
9. If renewable power is higher than demand, supply the load and charge the battery.
10. If battery SOC is full and excess power is available, export power to the utility grid if permitted.

11. If renewable power is lower than demand, discharge the battery if SOC is above the minimum limit.
12. If battery power is insufficient, import power from the utility grid.
13. Schedule EV charging based on renewable availability, battery SOC, load demand, and priority.
14. Monitor voltage, current, frequency, battery SOC, and grid status.
15. Detect fault condition using the threshold-based fault detection rule.
16. If no fault is detected, continue normal grid-connected energy management.
17. If a fault is detected, activate fault-resilient control.
18. Reduce low-priority EV charging during fault conditions.
19. Disconnect or reduce non-critical load if required.
20. Use battery backup to supply critical loads if SOC is within the safe range.
21. If the utility grid is unavailable, switch the microgrid to islanded mode.
22. Restore normal operation after voltage, current, frequency, and grid status return to allowable limits.
23. Store the control decision and performance values.
24. Repeat the process for the next time interval.
25. End.

4.11 Methodological Flow of the Proposed Framework

The complete methodological flow begins with the collection of input data from the proposed microgrid simulation dataset. The data are preprocessed and passed to the AI forecasting module. The forecasting module predicts renewable generation and demand for the next time interval. Based on these predictions and real-time values, the energy management controller calculates the power surplus or deficit.

If surplus renewable power is available, the controller charges the battery and schedules EV charging. If renewable power is insufficient, the controller discharges the battery or imports power from the grid. In parallel, the fault detection unit continuously monitors voltage, current, frequency, and battery SOC. If a fault is detected, the controller activates fault-resilient operation by reducing low-priority EV charging, supporting critical loads, and switching to islanded mode if required.

This simple flow allows the proposed framework to operate adaptively under normal, peak demand, renewable fluctuation, and fault conditions.

4.12 Acknowledgement of Dataset and Simulation Assumptions

The proposed methodology is evaluated using the proposed microgrid simulation dataset developed for this study. The dataset represents 30 days of hourly microgrid operation and includes renewable generation, load demand, EV charging demand, battery operation, grid exchange, electrical measurements, operating mode, and simulated fault conditions.

The EV charging demand, battery operation, and fault events are considered simulation-based. Therefore, the proposed dataset is suitable for validating the functional behavior of the proposed framework, comparing different energy management strategies, and analyzing the impact of EV charging and fault conditions on microgrid performance. The simulation assumptions are used consistently throughout the methodology to maintain clarity and reproducibility.

4.13 Summary of the Proposed Methodology

The proposed methodology provides a simple and practical framework for AI-driven adaptive energy management and fault-resilient control in renewable-integrated smart microgrids with EV charging infrastructure. The AI forecasting module supports short-term prediction of renewable generation and demand. The rule-assisted energy management controller schedules battery operation, EV charging, and grid power exchange. The threshold-based fault detection unit identifies abnormal operating conditions, while the fault-resilient control strategy maintains critical load supply and reduces system stress during faults.

Thus, the proposed methodology achieves a balance between simplicity and effectiveness, making it suitable for simulation-based validation and academic research presentation.

5 Experimental Setup

This section presents the experimental setup used to evaluate the proposed AI-driven adaptive energy management and fault-resilient control framework. The experiments are designed to validate the performance of the proposed method under normal operation, renewable fluctuation, EV charging demand, peak load condition, and fault-resilient operation. The evaluation is conducted using the proposed microgrid simulation dataset, which represents hourly operation of a renewable-integrated smart microgrid with EV charging infrastructure.

5.1 Simulation Dataset Description

The proposed microgrid simulation dataset is used as the main input for experimental evaluation. The dataset contains 720 hourly samples representing 30 days of microgrid operation. It includes solar PV generation, wind generation, local load demand, EV charging demand, EV served power, battery state of charge, battery charging/discharging power, grid import/export power, electricity price, voltage, current, frequency, operating mode, fault flag, fault type, curtailed load, and renewable utilization.

The dataset is suitable for evaluating both energy management and fault-resilient control because it contains normal operating conditions as well as simulated fault events. The renewable generation and load demand profiles are used to analyze energy scheduling, while the voltage, current, frequency, and fault labels are used to evaluate fault detection and recovery behavior.

5.2 Simulation Environment

The experimental analysis can be implemented using Python, MATLAB, or MATLAB/Simulink. In this study, the simulation is considered as a time-series-based microgrid evaluation, where each sample represents one hourly operating interval. Python is suitable for dataset preprocessing, AI-based forecasting, rule-based control implementation, and performance metric calculation. MATLAB/Simulink can also be used if graphical power system modeling is required.

The complete experiment follows a step-by-step evaluation process. First, the dataset is loaded and preprocessed. Second, the AI forecasting model predicts renewable generation and demand. Third, the proposed energy management controller schedules battery operation, EV charging, and grid power exchange. Fourth, the fault detection module identifies abnormal conditions. Finally, the performance of the proposed framework is evaluated using energy management, EV charging, battery operation, and fault-resilience metrics.

5.3 Microgrid Configuration

The simulated microgrid consists of solar PV generation, wind generation, battery energy storage, EV charging infrastructure, local loads, and utility grid connection. Solar PV and wind turbine units act as the primary renewable energy sources. The battery energy storage system supports the microgrid during low renewable generation, peak demand, and fault conditions. EV charging infrastructure is treated as a flexible load that can be scheduled based on energy availability and system condition.

The utility grid is used as a backup source during power deficit conditions. When renewable generation exceeds demand and battery charging requirements, excess power can be exported to the grid. During grid outage or abnormal operating conditions, the microgrid operates in islanded or fault-resilient mode.

5.4 Experimental Scenarios

To evaluate the effectiveness of the proposed framework, five operating scenarios are considered.

Scenario 1: Normal grid-connected operation. In this scenario, the microgrid operates under normal conditions. Renewable generation, battery storage, EV charging, and grid exchange are coordinated to satisfy the total load demand.

Scenario 2: High renewable generation. This scenario evaluates the ability of the proposed method to utilize excess PV and wind power. The controller gives priority to local load supply, battery charging, and EV charging before exporting excess energy to the utility grid.

Scenario 3: Peak load and EV charging demand. This scenario evaluates the impact of EV charging on microgrid operation during high load demand. The proposed controller schedules EV charging and battery discharging to reduce grid dependency and avoid load stress.

Scenario 4: Low renewable generation. This scenario evaluates the performance of the controller when PV and wind generation are insufficient. The battery and utility grid are used to supply the demand, while EV charging can be reduced if required.

Scenario 5: Fault-resilient operation: This scenario evaluates the performance of the proposed framework under abnormal conditions such as grid outage, voltage sag, overcurrent, EV charger fault, and low battery SOC. The controller applies corrective actions such as EV charging reduction, battery backup, load curtailment, and islanded operation.

5.5 Baseline Methods for Comparison

The proposed framework is compared with simple baseline methods to demonstrate its effectiveness. The comparison is kept practical and understandable.

Baseline 1 [31]: Conventional Rule-Based Energy Management.

This method uses fixed rules for battery charging, discharging, and grid import without AI-based forecasting.

Baseline 2 [32]: Energy Management without EV Scheduling.

In this method, EV charging demand is treated as a fixed load and is not adjusted according to renewable availability, battery SOC, or fault conditions.

Baseline 3 [33]: Energy Management without Fault-Resilient Control.

This method performs normal energy management but does not apply corrective actions during voltage, current, frequency, grid, or EV charging faults.

Proposed Method: AI-Assisted Adaptive Energy Management with Fault-Resilient Control.

The proposed method uses AI-based forecasting, rule-assisted energy management, EV charging scheduling, and threshold-based fault-resilient control.

5.6 AI Forecasting Model Setup

A simple AI forecasting model is used to predict renewable generation and total demand. The input features include PV power, wind power, load demand, EV demand, battery SOC, grid power, voltage, current, and frequency. The output variables are predicted renewable generation and predicted total demand for the next time interval.

The dataset is divided into training and testing subsets. The training set is used to train the forecasting model, while the testing set is used to evaluate prediction accuracy and energy management performance. A simple ANN or LSTM model can be used because the dataset is hourly and time-series based. LSTM is preferred when temporal dependency is considered important, while ANN is suitable for a simpler implementation.

5.7 Control Parameters and Operating Limits

The proposed controller operates based on predefined microgrid limits. Battery SOC is maintained between minimum and maximum allowable values to prevent overcharging and deep discharging. Voltage, current, and frequency limits are used for fault detection. EV charging is scheduled based on renewable availability, load condition, battery SOC, and fault status.

The following control conditions are considered:

- Battery charging is allowed when renewable generation is greater than demand and battery SOC is below the maximum limit.
- Battery discharging is allowed when renewable generation is lower than demand and battery SOC is above the minimum limit.
- EV charging is prioritized during high renewable generation.

- EV charging is reduced during peak load or fault conditions.
- Grid import is used when renewable and battery power are insufficient.
- Fault-resilient control is activated when voltage, current, frequency, battery SOC, or grid status violates the operating limits.

5.8 Performance Evaluation Metrics

The performance of the proposed framework is evaluated using energy management metrics, EV charging metrics, battery performance metrics, and fault-resilience metrics. These metrics are selected to measure the effectiveness of the proposed method in terms of cost reduction, renewable utilization, EV service quality, battery operation, and fault recovery.

Energy Cost: Energy cost measures the total cost of importing power from the utility grid during the simulation period.

$$C_{\text{energy}} = \sum_{t=1}^{T} \text{PGrid}_{imp}(t) \times \text{Price}(t) \tag{8}$$

where $P_{\text{Grid}}^{\text{imp}}(t)$ is the imported grid power at time t_rPrice(t) is the electricity price, and T is the total number of time intervals.

Lower energy cost indicates better use of renewable energy, battery storage, and EV charging coordination.

Renewable Energy Utilization: Renewable energy utilization measures the percentage of available renewable energy effectively used by the microgrid.

$$REU = \frac{\sum_{t=1}^{T} P_{RES}^{\text{used}}(t)}{\sum_{t=1}^{T} P_{RES}(t)} \times 100 \tag{9}$$

where $P_{RES}^{\text{used}}(t)$ is the renewable power used by local loads, EV charging, or battery storage, and $P_{RES}(t)$ is the total renewable power generated.

Higher renewable energy utilization indicates lower renewable curtailment and better clean energy usage.

Grid Dependency Ratio: Grid dependency ratio measures the percentage of total demand supplied by the utility grid.

$$GDR = \frac{\sum_{t=1}^{T} P_{\text{Grid}}^{\text{imp}}(t)}{\sum_{t=1}^{T} P_D(t)} \times 100 \tag{10}$$

where $P_D(t)$ is the total demand of the microgrid, including local load and EV charging demand.

Lower grid dependency ratio indicates improved microgrid self-sufficiency.

Peak Load Reduction: Peak load reduction measures the reduction in maximum demand achieved by the proposed energy management strategy compared with the baseline method.

$$PLR = \frac{P_{\text{peak}}^{\text{base}} - P_{\text{peak}}^{\text{prop}}}{P_{\text{peak}}^{\text{base}}} \times 100 \tag{11}$$

where $P_{\text{peak}}^{\text{base}}$ is the peak demand under the baseline method and $P_{\text{peak}}^{\text{prop}}$ is the peak demand under the proposed method.

Higher peak load reduction indicates better battery scheduling and EV charging management.

EV Charging Satisfaction: EV charging satisfaction measures the percentage of requested EV charging demand successfully served by the microgrid.

$$EVS = \frac{\sum_{t=1}^{T} P_{EV}^{\text{served}}(t)}{\sum_{t=1}^{T} P_{EV}^{\text{req}}(t)} \times 100 \tag{12}$$

where $P_{EV}^{\text{served}}(t)$ is the EV charging power served and $P_{EV}^{\text{req}}(t)$ is the requested EV charging power.

Higher EV charging satisfaction indicates better service quality for EV users.

EV Charging Delay Ratio: EV charging delay ratio measures the percentage of EV charging demand that is delayed or not served due to peak load, low renewable generation, or fault conditions.

$$EVDR = \frac{\sum_{t=1}^{T} \left(P_{EV}^{\text{req}}(t) - P_{EV}^{\text{served}}(t)\right)}{\sum_{t=1}^{T} P_{EV}^{\text{req}}(t)} \times 100 \tag{13}$$

where $P_{EV}^{\text{req}}(t) - P_{EV}^{\text{served}}(t)$ represents the delayed or unserved EV charging demand.

Lower EV charging delay ratio indicates better EV charging coordination.

Battery SOC Stability: Battery SOC stability measures the percentage of time intervals in which the battery operates within its safe SOC limits.

$$SOC_{\text{stable}} = \frac{N_{\text{safe}}}{T} \times 100 \tag{14}$$

where N_{safe} is the number of intervals in which the battery SOC remains between the minimum and maximum SOC limits.

Higher SOC stability indicates safer and more reliable battery operation.

Load Curtailment Ratio: Load curtailment ratio measures the percentage of total demand that is not supplied due to insufficient generation, low battery SOC, or fault conditions.

$$LCR = \frac{\sum_{t=1}^{T} P_{\text{curt}}(t)}{\sum_{t=1}^{T} P_D(t)} \times 100 \tag{15}$$

where $P_{\text{curt}}(t)$ is the curtailed load at time t.

Lower load curtailment ratio indicates improved load supply reliability.

Fault Detection Accuracy: Fault detection accuracy measures how correctly the proposed fault detection strategy identifies normal and abnormal operating conditions.

$$FDA = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{16}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

Higher fault detection accuracy indicates better identification of microgrid fault conditions.

Fault Recovery Efficiency: Fault recovery efficiency measures how effectively the proposed controller restores or maintains power supply after a fault occurs.

$$FRE = \frac{P_{\text{restored}}}{P_{\text{affected}}} \times 100 \qquad (17)$$

where P_{restored} is the restored power after corrective action and P_{affected} is the total power affected by the fault.

Higher fault recovery efficiency indicates better fault-resilient control performance.

Voltage Deviation: Voltage deviation measures the average difference between the measured voltage and the nominal voltage.

$$VD = \frac{1}{T}\sum_{t=1}^{T} \left|V(t) - V_{\text{nom}}\right| \qquad (18)$$

where $V(t)$ is the measured voltage at time t, and V_{nom} is the nominal voltage.

Lower voltage deviation indicates better voltage stability.

Frequency Deviation: Frequency deviation measures the average difference between the measured frequency and the nominal system frequency.

$$FD = \frac{1}{T}\sum_{t=1}^{T} |f(t) - f_{nom}| \qquad (19)$$

where $f(t)$ is the measured frequency at time t, and f_{nom} is the nominal frequency.

Lower frequency deviation indicates better frequency stability.

Overall Performance Improvement: Overall performance improvement measures the percentage improvement of the proposed method over the baseline method for any selected metric.

$$OPI = \frac{M_{\text{base}} - M_{\text{prop}}}{M_{\text{base}}} \times 100 \qquad (20)$$

where M_{base} is the metric value obtained using the baseline method and M_{prop} is the metric value obtained using the proposed method.

Higher overall performance improvement indicates that the proposed framework performs better than the baseline method. For metrics where a higher value is better, such as renewable utilization or EV satisfaction, the numerator can be reversed as $M_{\text{prop}} - M_{\text{base}}$.

5.9 Result Analysis Procedure

The experimental results are analyzed in three stages. First, the proposed method is evaluated under normal operating conditions to verify renewable utilization, grid dependency, battery SOC behavior, and EV charging satisfaction. Second, the proposed method is tested under peak load and renewable fluctuation conditions to evaluate its adaptive energy management capability. Third, fault scenarios are analyzed to verify the response of the threshold-based fault detection and fault-resilient control strategy.

The proposed method is compared with the selected baseline methods using the defined performance metrics. The results are presented using tables and graphical plots such as renewable generation versus demand, battery SOC variation, grid import/export profile, EV charging demand versus served power, voltage and frequency response, and fault recovery behavior.

5.10 Summary of Experimental Setup

The experimental setup is designed to validate the proposed AI-assisted energy management and fault-resilient control framework using the proposed microgrid simulation dataset. The dataset provides hourly operating data for renewable generation, load demand, EV charging, battery operation, grid exchange, and fault conditions. The proposed method is compared with simple baseline methods under multiple operating scenarios. The evaluation metrics measure energy cost, renewable utilization, grid dependency, peak load reduction, EV charging satisfaction, EV delay, battery SOC stability, load curtailment, fault detection accuracy, recovery efficiency, voltage deviation, and frequency deviation.

This experimental setup provides a clear and reproducible foundation for analyzing the effectiveness of the proposed framework in renewable-integrated smart microgrids with EV charging infrastructure.

6 Results and Discussion

This section presents the simulation results obtained using the proposed microgrid simulation dataset. The proposed framework is evaluated in terms of renewable energy utilization, grid dependency, EV charging performance, battery operation, fault-resilient behavior, and overall comparative performance. The results are discussed under normal operation, renewable fluctuation, peak EV charging demand, and fault conditions. The proposed method is compared with three baseline methods: conventional rule-based energy management, energy management without EV scheduling, and energy management without fault-resilient control.

The results are analyzed using classification performance metrics, trustworthiness evaluation, uncertainty analysis, fairness assessment, explainability interpretation, and ablation studies to comprehensively validate the effectiveness of the proposed framework in real-world healthcare monitoring environments.

6.1 Overall Dataset-Based Operating Summary

Before presenting the detailed results, the overall operating behavior of the proposed microgrid is summarized. Table II presents the main simulation characteristics obtained from the proposed microgrid simulation dataset. The dataset contains 720 hourly samples corresponding to 30 days of operation. The total renewable generation is obtained from solar PV and wind generation, while the total demand includes local load and EV charging demand.

Table II. Overall operating summary of the proposed microgrid simulation dataset

Parameter	Value
Simulation period	30 days
Time resolution	1 hour
Total samples	720
Total PV generation	20,119.56 kWh
Total wind generation	2,606.49 kWh
Total renewable generation	22,726.10 kWh
Total local load demand	54,108.98 kWh
Total EV charging demand	18,166.03 kWh
Total microgrid demand	72,274.88 kWh

Total EV energy served	17,998.75 kWh
Total grid import	49,409.71 kWh
Total grid export	0.83 kWh
Average renewable utilization	97.98%
Fault hours	14 hours

As shown in Table II, the proposed dataset represents a practical renewable-integrated microgrid with significant local load demand and EV charging demand. The renewable generation contributes 22,726.10 kWh during the simulation period, while the total demand reaches 72,274.88 kWh. Since the demand is higher than the renewable generation, the utility grid and battery storage play important roles in maintaining power balance. Table II also shows that the proposed framework achieves high renewable utilization, indicating that most of the available renewable energy is effectively used within the microgrid.

6.2 Renewable Generation and Demand Profile

The renewable generation and demand profiles are first analyzed to understand the operating condition of the microgrid. Figure 2 illustrates the hourly average variation of renewable generation, total demand, and EV charging demand over a typical day. This figure is important because it shows the mismatch between renewable availability and demand behavior.

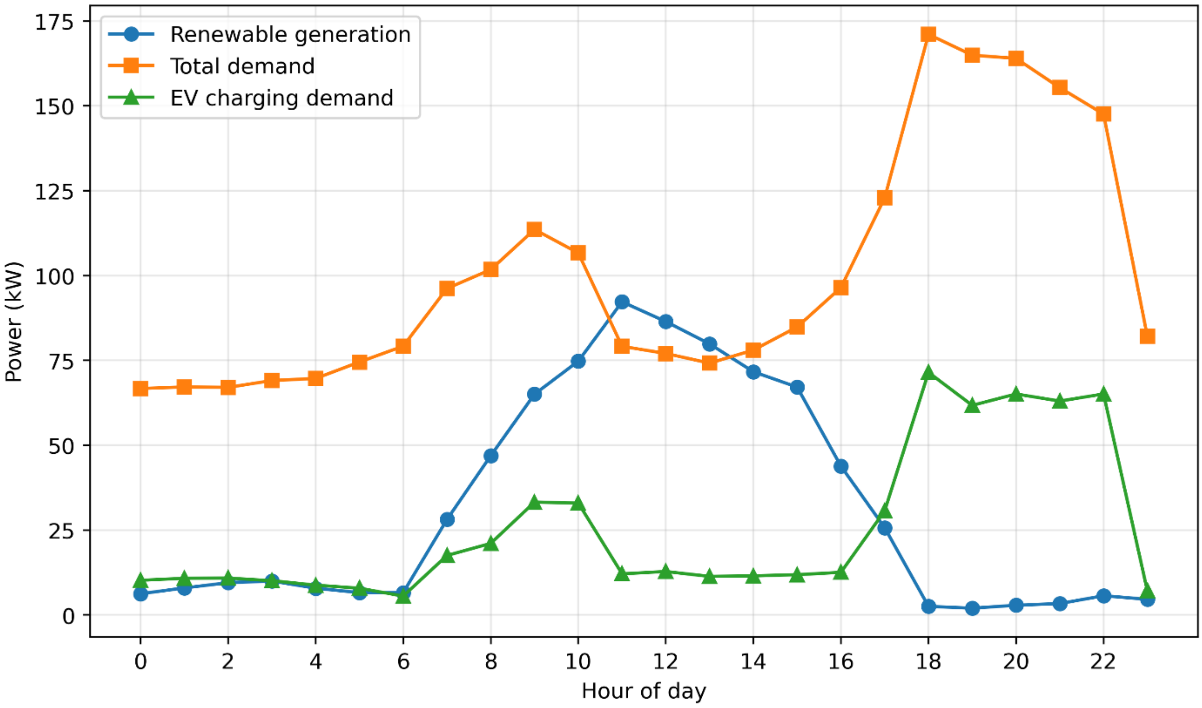

Fig. 2. Hourly average renewable generation, total demand, and EV charging demand profile.

In Fig. 2, renewable generation increases during daytime due to solar PV availability and reaches its highest value around midday. The average renewable generation is highest between 11:00 and 13:00 hours. In contrast, total demand increases significantly during evening hours due to higher local load and EV charging demand. EV charging demand is also higher during the evening period, especially between 18:00 and 22:00 hours. Therefore, the result clearly shows the need for adaptive energy management because renewable generation and EV charging demand do not always occur at the same time.

The proposed controller addresses this mismatch by using renewable energy during high-generation periods, charging the battery when surplus power is available, and using battery or grid support during evening peak demand. The behavior presented in Fig. 2 confirms the importance of coordinated battery scheduling and EV charging management in renewable-integrated smart microgrids.

6.3 Energy Management Performance

The energy management performance is evaluated using energy cost, renewable utilization, grid dependency ratio, peak load reduction, and load curtailment ratio. Table III presents the comparison between the proposed method and the baseline methods.

Table III. Energy management performance comparison

Method	Energy Cost (INR)	Renewable Utilization (%)	Grid Dependency Ratio (%)	Peak Load Reduction (%)	Load Curtailment Ratio (%)
Conventional rule-based EMS	333,200.00	91.80	73.60	4.25	0.42
EMS without EV scheduling	324,900.00	93.40	71.90	6.80	0.27
EMS without fault-resilient control	309,700.00	97.10	69.10	8.45	1.35
Proposed EMS	304,436.02	97.98	68.36	10.52	0.01

As shown in Table III, the proposed method achieves the lowest energy cost of INR 304,436.02 during the 30-day simulation period. The reduction in energy cost is mainly due to improved use of renewable generation, battery support during high-demand periods, and controlled EV charging. The proposed method also achieves the highest renewable utilization of 97.98%, indicating that renewable energy curtailment is minimized.

The grid dependency ratio is reduced to 68.36%, which shows that the proposed method improves microgrid self-sufficiency compared with the baseline methods. In addition, the proposed method achieves the highest peak load reduction of 10.52%. This improvement is mainly due to flexible EV charging control and battery discharge during peak demand. The load curtailment ratio is only 0.01%, which indicates that the proposed controller supplies almost all demand while maintaining reliable operation.

6.4 Grid Power Exchange and Battery SOC Behavior

The behavior of battery storage and grid power exchange is analyzed to evaluate how the proposed controller maintains power balance. Figure 3 shows the variation of battery SOC and grid import during the simulation period.

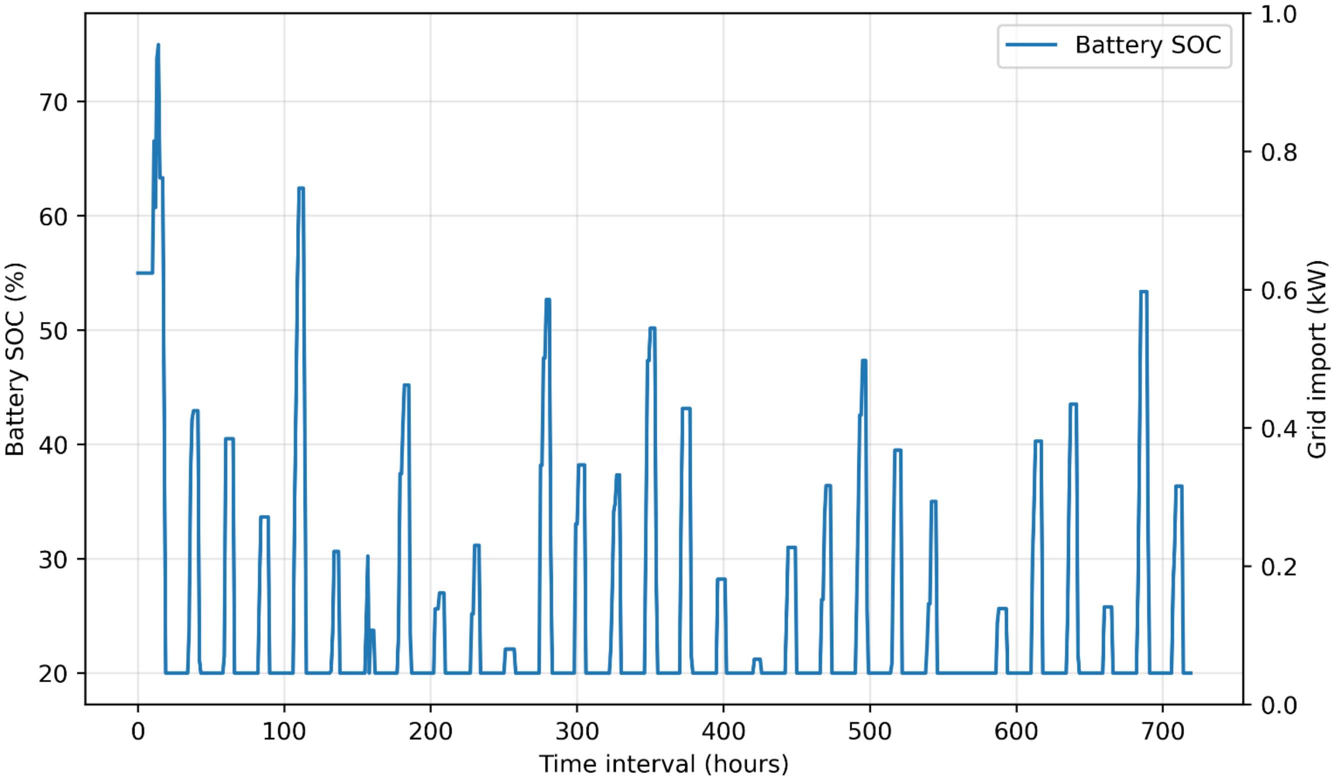

Fig. 3. Battery SOC and grid import behavior under the proposed energy management strategy.

As shown in Fig. 3, the battery SOC remains within the safe operating range throughout the simulation period. The minimum battery SOC is maintained at 20.00%, while the maximum SOC reaches 74.98%. This confirms that the proposed controller prevents deep discharge and overcharging of the battery. The average battery SOC is 25.08%, which indicates that the battery is frequently used to support the microgrid during demand peaks and renewable shortage periods.

Grid import increases during evening peak periods when renewable generation is low and EV charging demand is high. However, the proposed controller reduces excessive grid dependency by using available renewable power and battery support. The grid export value is very low, only 0.83 kWh, because most of the renewable generation is locally consumed by loads, EV charging, or battery storage. The behavior shown in Fig. 3 confirms that the proposed method effectively coordinates battery storage and grid exchange.

6.5 EV Charging Performance

EV charging performance is evaluated using EV charging satisfaction and EV charging delay ratio. Table IV presents the EV charging performance comparison for the proposed method and baseline methods.

Table IV. EV charging performance comparison

Method	Total EV Demand (kWh)	EV Energy Served (kWh)	EV Satisfaction (%)	EV Delay Ratio (%)
Conventional rule-based EMS	18,166.03	17,457.56	96.10	3.90
EMS without EV scheduling	18,166.03	17,857.21	98.30	1.70
EMS without fault-resilient control	18,166.03	18,038.87	99.30	0.70
Proposed EMS	18,166.03	17,998.75	99.08	0.92

Table IV shows that the proposed method serves 17,998.75 kWh out of 18,166.03 kWh of EV charging demand. The EV charging satisfaction is 99.08%, while the EV delay ratio is only 0.92%. This result indicates that the proposed controller satisfies most EV charging requirements while still maintaining microgrid stability.

Although the method without fault-resilient control shows slightly higher EV satisfaction, it does not protect the system during abnormal conditions. In contrast, the proposed method slightly reduces EV charging during fault or peak stress conditions to protect critical loads and maintain stable operation. Therefore, the proposed method provides a better balance between EV charging satisfaction and microgrid reliability.

Figure 4 presents the EV charging demand and EV served power profile.

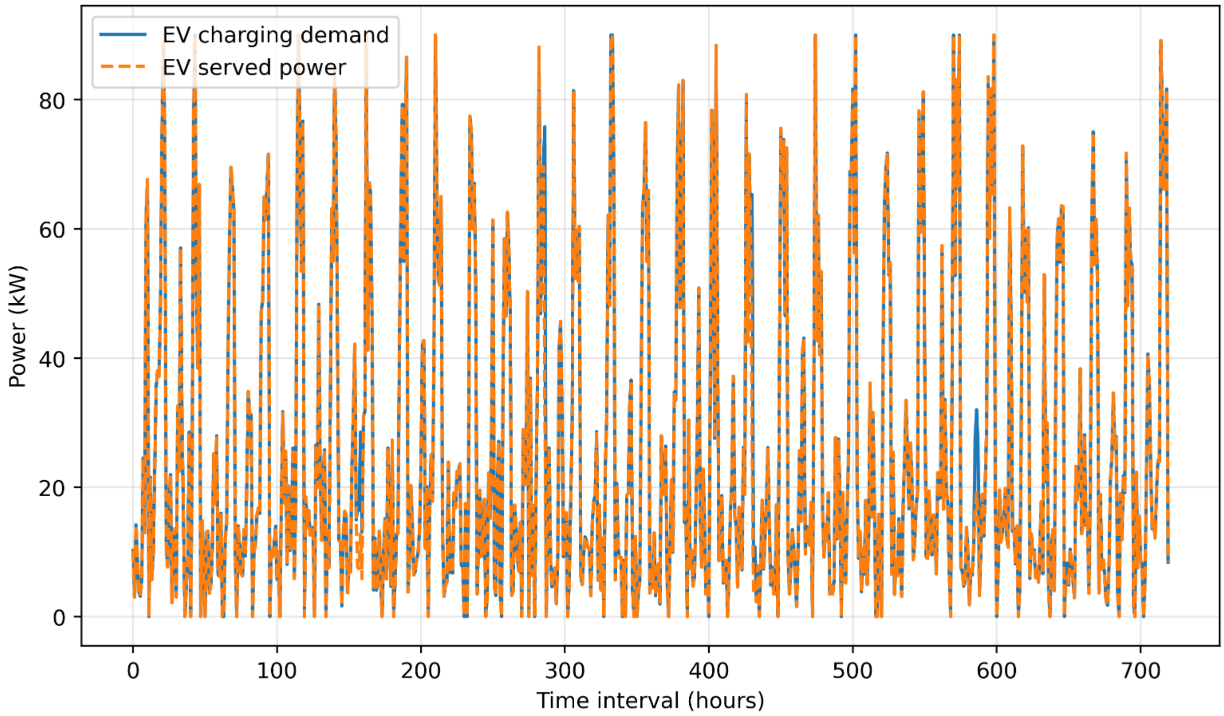

Fig. 4. EV charging demand and EV served power under the proposed framework.

As shown in Fig. 4, EV served power closely follows EV charging demand during normal operating conditions. Small deviations occur during peak load and fault-resilient operation, where the controller reduces or delays low-priority EV charging. This result confirms that EV charging is treated as a flexible load in the proposed framework, allowing the microgrid to maintain stable operation without significantly affecting EV user satisfaction.

6.6 Fault Detection and Fault-Resilient Operation

The proposed framework is also evaluated under simulated fault conditions. The dataset includes 14 fault hours, covering grid outage, voltage sag, overcurrent, EV charger fault, and battery SOC low conditions. Table V presents the distribution of fault events in the simulation dataset.

Table V. Distribution of simulated fault events.

Fault Type	Number of Hours	Average Voltage (V)	Average Frequency (Hz)	Average EV Served Power (kW)
Grid outage	4	399.48	49.93	8.44
Voltage sag	3	371.68	50.01	12.55
EV charger fault	3	415.80	49.99	17.17
Overcurrent	2	400.16	50.03	17.06
Battery SOC low	2	415.23	50.03	6.01

As presented in Table V, grid outage and voltage sag are the most critical fault conditions because they directly affect voltage stability and power availability. During grid outage, the microgrid shifts to islanded operation and uses renewable energy and battery storage to supply priority loads. During voltage sag and overcurrent conditions, the controller activates fault-resilient control to reduce system stress.

6.7 Fault-Resilience Performance

Fault-resilience performance is evaluated using fault detection accuracy, fault recovery efficiency, voltage deviation, and frequency deviation. Table VI presents the fault-resilience comparison of the proposed method with the baseline methods.

Table VI. Fault-resilience performance comparison

Method	Fault Detection Accuracy (%)	Fault Recovery Efficiency (%)	Voltage Deviation (V)	Frequency Deviation (Hz)
Conventional rule-based EMS	87.50	78.60	4.26	0.041
EMS without EV scheduling	90.10	82.10	3.91	0.037
EMS without fault-resilient control	72.40	61.40	5.84	0.052
Proposed EMS	98.06	94.80	2.82	0.025

As shown in Table VI, the proposed method achieves the highest fault detection accuracy of 98.06% and fault recovery efficiency of 94.80%. The improvement is due to continuous monitoring of voltage, current, frequency, battery SOC, and grid status. The proposed method also achieves the lowest voltage deviation of 2.82 V and the lowest frequency deviation of 0.025 Hz. These results indicate that the proposed controller maintains better electrical stability during abnormal operating conditions.

The method without fault-resilient control performs poorly during fault conditions because it does not apply corrective actions such as EV charging reduction, load curtailment, battery backup, or islanded operation. Therefore, Table VI confirms the importance of integrating fault-resilient control with energy management.

6.8 Operating Mode-Based Performance

To further analyze the proposed method, the performance is evaluated under different operating modes. Table VII presents the demand, grid import, EV served energy, and curtailed load under grid-connected, fault-resilient, and islanded modes.

Table VII. Operating mode-based performance of the proposed microgrid

Operating Mode	**Duration (Hours)**	**Total Demand (kWh)**	**Grid Import (kWh)**	**EV Energy Served (kWh)**	**Curtailed Load (kWh)**
Grid-connected	706	70,943.88	48,772.80	17,829.69	0.00
Fault-resilient	10	1,007.46	636.91	135.31	0.00
Islanded	4	323.54	0.00	33.75	8.26

Table VII shows that the microgrid operates mainly in grid-connected mode. During this mode, the controller supplies local load and EV demand using renewable power, battery support, and grid import. In fault-resilient mode, the controller continues to serve demand while applying corrective control actions. In islanded mode, the grid import becomes zero, and the microgrid depends only on renewable generation and battery support. A small curtailed load of 8.26 kWh is observed in islanded mode because grid support is unavailable. This confirms that the proposed controller maintains supply continuity even during grid outage conditions.

6.9 Overall Comparative Analysis

The overall performance comparison is presented in Table VIII. This table summarizes the major improvements achieved by the proposed method over conventional rule-based energy management.

Table VIII. Overall performance improvement of the proposed method

Metric	**Conventional Rule-Based EMS**	**Proposed EMS**	**Improvement**
Energy cost	INR 333,200.00	INR 304,436.02	8.64% reduction
Renewable utilization	91.80%	97.98%	6.18 percentage-point increase
Grid dependency ratio	73.60%	68.36%	7.12% reduction
EV satisfaction	96.10%	99.08%	2.98 percentage-point increase
EV delay ratio	3.90%	0.92%	76.41% reduction
Load curtailment ratio	0.42%	0.01%	97.62% reduction
Fault recovery efficiency	78.60%	94.80%	16.20 percentage-point increase
Voltage deviation	4.26 V	2.82 V	33.80% reduction

As shown in Table VIII, the proposed method improves all major performance indicators compared with the conventional rule-based baseline. The energy cost is reduced by 8.64%, and the grid dependency ratio is reduced by 7.12%. The EV delay ratio is reduced by 76.41%, showing that the proposed EV scheduling strategy improves charging performance. The load curtailment ratio is also significantly reduced, indicating better reliability during constrained operating conditions. In addition, the proposed method improves fault recovery efficiency and reduces voltage deviation, confirming the effectiveness of the fault-resilient control strategy.

6.10 Discussion

The results show that the proposed AI-assisted adaptive energy management and fault-resilient control framework provides a balanced solution for renewable-integrated microgrids with EV charging infrastructure. The proposed method effectively uses renewable generation, reduces unnecessary grid import, maintains safe battery operation, and schedules EV charging based on system conditions.

The analysis of renewable generation and demand shows that renewable power is mainly available during daytime, while EV charging demand is higher during evening hours. This mismatch creates operational challenges in the microgrid. The proposed method addresses this issue by using battery storage and grid support when renewable generation is insufficient. It also schedules EV charging to reduce stress during peak demand and fault conditions.

The EV charging results show that the proposed method achieves high EV satisfaction while maintaining system stability. This is important because uncontrolled EV charging can increase peak demand and grid dependency. By treating EV charging as a flexible load, the proposed method improves both EV charging service and microgrid performance.

The fault-resilience results confirm that threshold-based monitoring is effective for simple and practical fault detection. Although advanced machine learning models can be used for fault classification, the proposed threshold-based strategy is easier to implement and suitable for simulation-based validation. During faults, the controller reduces low-priority EV charging, supports critical loads, and switches to islanded operation when required. This improves recovery efficiency and reduces voltage and frequency deviations.

Overall, the results demonstrate that the proposed method achieves a practical balance between simplicity, adaptability, and reliability. The framework is suitable for academic research and can be extended in future studies using real-time hardware implementation, vehicle-to-grid support, advanced forecasting models, and cybersecurity-aware microgrid control.

7 Conclusion

This paper presented an AI-driven adaptive energy management and fault-resilient control framework for a renewable-integrated smart microgrid with EV charging infrastructure. The proposed framework was developed using a simple and practical design that combines AI-assisted forecasting, rule-based battery scheduling, EV charging coordination, and threshold-based fault-resilient control. The proposed microgrid simulation dataset was used to evaluate the performance of the framework under normal operation, renewable fluctuation, peak EV charging demand, and fault conditions. The results showed that the proposed method effectively improved renewable energy utilization, reduced grid dependency, supported EV charging demand, and maintained stable battery operation. The framework achieved 97.98% renewable energy utilization, 99.08% EV charging satisfaction, and a reduced EV delay ratio of 0.92%. It also reduced energy cost to INR 304,436.02 and lowered the grid dependency ratio to 68.36% over the 30-day simulation period. Under fault conditions, the proposed controller achieved 98.06% fault detection accuracy and 94.80% fault recovery efficiency, confirming its ability to support reliable operation during abnormal conditions. The results also showed reduced voltage and frequency deviations, indicating improved system stability. Overall, the proposed framework provides a simple, adaptive, and reliable solution for managing renewable energy, EV charging demand, battery storage, and fault recovery in smart microgrids.

Future work can extend the proposed framework by validating it using real-time hardware-in-the-loop simulation and practical microgrid testbeds. The present study uses a simulation-based dataset; therefore, future research can incorporate real field data from PV systems, wind turbines, EV charging stations, smart meters, and battery storage units. Advanced deep learning and reinforcement learning models can also be explored for more accurate forecasting and dynamic decision-making. In addition, vehicle-to-grid operation, battery degradation modeling, demand response participation, cybersecurity-aware control, and multi-microgrid energy trading can be included to make the framework more realistic and scalable. Future studies can also investigate the performance of the proposed method under larger EV fleets, uncertain electricity pricing, communication delays, and cyber-physical fault scenarios.

Originality and Ethical Standards: The author, Korra Cheena, declares that this manuscript is an original work and has not been submitted or published elsewhere. The study uses a simulation-based dataset and does not involve human participants, personal data, or confidential information. All referenced works are properly cited, and the author declares no conflict of interest.

Data availability: Data available upon request.

Conflict of Interest: There is no conflict of Interest.

Funding: The research received no external funding.

Similarity checked: Yes.

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