www.ijarp.com ISSN 2456-9992 Page: 01-37

International Journal Advanced Research Publications

Research Article

Volume: 02
Issue: 07

ARTIFICIAL INTELLIGENCE-BASED ENERGY MANAGEMENT FOR HYBRID RENEWABLE SYSTEMS WITH BATTERY OPTIMIZATION AND SMART GRID STABILITY ENHANCEMENT

***Niraj Mishra**

Government Girls Polytechnic, Amethi, UP, India.

Article Received: 13 June 2026, Article Revised: 03 July 2026, Published on: 23 July 2026

***Corresponding Author: Niraj Mishra**

Government Girls Polytechnic, Amethi, UP, India.

Doi: https://doi-doi.org/101555/ijarp.5434

ABSTRACT

This paper proposes an AI-assisted smart grid energy management system (EMS) for coordinated operation of solar PV, wind, hydro, biomass, fuel cell, battery energy storage and utility grid support. The proposed framework is implemented in MATLAB/Simulink and compared to a conventional renewable-energy management approach in a 24-hour operating horizon. The system comprises a 100 kW PV array, 120 kW wind turbine, 130 kW hydro unit, 90 kW biomass plant, 60 kW fuel cell and 300 kWh battery energy storage system with SOC limits of 20–90%.The proposed AI-assisted EMS performs adaptive dispatch, battery coordination and bidirectional grid interaction based on renewable availability, load demand and battery state of charge, whereas the conventional technique is based on independent renewable-source operation. The simulation results show that the overall. Simulation results indicate that total renewable generation reaches approximately 320–340 kW against a load demand of 110–180 kW. The battery SOC varies between 20% and 90%, while maximum charging/discharging power reaches 80 kW. Grid import and export are effectively managed within 100–120 kW and 100 kW, respectively. Furthermore, system voltage remains close to 1.0 pu and frequency near 50 Hz, demonstrating stable operation. The results confirm that the proposed AI-assisted framework improves renewable-energy utilization, enhances battery management, reduces grid dependency, and provides superior operational stability compared with the conventional approach.

KEYWORDS: Artificial Intelligence (AI), Battery Energy Storage System (BESS), Biomass Energy, Grid Import and Export, Hybrid Renewable Energy System, Hydropower, Renewable

Energy Integration, Smart Grid Energy Management System, Solar Photovoltaic (PV), State of Charge (SOC), Sustainable Smart Grid, Wind Energy.

NOMENCLATURE

A. Abbreviations

Abbreviation	Description
AI	Artificial Intelligence
ANN	Artificial Neural Network
BESS	Battery Energy Storage System
BMS	Battery Management System
DER	Distributed Energy Resources
EMS	Energy Management System
ESS	Energy Storage System
FC	Fuel Cell
HRES	Hybrid Renewable Energy System
ML	Machine Learning
MG	Microgrid
MPC	Model Predictive Control
MPPT	Maximum Power Point Tracking
PCC	Point of Common Coupling
PV	Photovoltaic
RES	Renewable Energy Sources
SG	Smart Grid
SOC	State of Charge
V2G	Vehicle-to-Grid

Symbol	Description	Unit
Δt	Sampling interval	h
E_max	Maximum battery energy capacity	kWh
f	System frequency	Hz
I_rr	Solar irradiance	W/m²
N	Number of simulation samples	–
P_bat	Battery charging/discharging power	kW
P_biomass	Biomass power output	kW
P_curtail	Curtailed renewable power	kW
P_fc	Fuel-cell power output	kW
P_gen	Total generated power	kW
P_grid_export	Grid exported power	kW

Symbol	Description	Unit
P_grid_import	Grid imported power	kW
P_hydro	Hydropower output	kW
P_load	Load demand	kW
P_pv	Solar photovoltaic power output	kW
P_ren	Total renewable power	kW
P_wind	Wind turbine power output	kW
SOC	Battery state of charge	%
SOC_max	Maximum allowable SOC	%
SOC_min	Minimum allowable SOC	%
t	Simulation time	h
T	Ambient temperature	°C
v	Wind speed	**m/s**
V_pu	Per-unit voltage	**pu**
η_ch	Battery charging efficiency	–
η_dis	Battery discharging efficiency	–

C. Subscripts **Subscript**	**Description**
bat	Battery energy storage system
biomass	Biomass generation system
ch	Charging mode
dis	Discharging mode
fc	Fuel cell system
grid	Utility grid
hydro	Hydropower system
load	Electrical load
max	Maximum value
min	Minimum value
pv	Solar photovoltaic system
ref	Reference value
ren	Renewable energy
wind	Wind energy system

1. INTRODUCTION

The global energy sector has undergone a remarkable transformation in the past few decades due to the rapid increase in electricity demand, depletion of fossil-fuel reserves, environmental pollution and climate-change concerns. Electric power systems have been traditionally heavily dependent on coal-, oil- and natural-gas-based generation systems. But these traditional energy sources release large amounts of greenhouse gases, contributing to global warming. The International Energy Agency (IEA) reports that the global electricity demand is growing steadily and renewable-energy technologies are expected to lead the future expansion of power systems [1].

Similarly, reports from the International Renewable Energy Agency (IRENA) indicate that worldwide renewable-energy deployment has reached unprecedented levels, with solar photovoltaic (PV) and wind energy emerging as the fastest-growing renewable technologies. Due to their clean, sustainable, and environmentally friendly nature, renewable-energy systems such as solar PV, wind, hydro, biomass, and hydrogen fuel cells are increasingly being integrated into modern power systems and smart grids.

Recent global renewable-energy statistics further highlight the urgency of developing advanced smart-grid energy-management solutions. According to IRENA Renewable Capacity Statistics and IEA Renewable Energy Market Updates, total installed renewable-energy capacity increased from approximately 2,799 GW in 2020 to about 4,448 GW in 2024, while global renewable deployment is projected to continue growing rapidly through 2026 [2], [3]. During the same period, solar PV capacity increased from nearly 760 GW in 2020 to more than 1,860 GW in 2024 and is projected to exceed 2,700 GW by 2026. Similarly, global wind-power capacity increased from approximately.

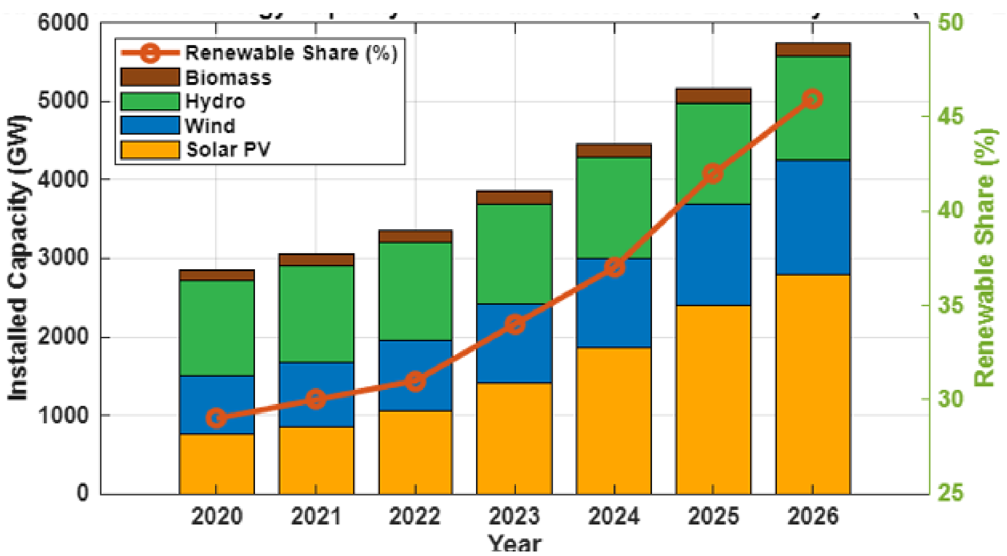

Fig. 1. Global Renewable Energy Capacity Growth and Technology-Wise Contribution (2020–2026).

743 GW in 2020 to more than 1,130 GW in 2024 and is expected to approach 1,450 GW by 2026. As shown in Fig. 1, the renewable energy capacity is increasing steadily with the

largest share of new installations being accounted for by solar PV followed by wind energy. The figure clearly shows the accelerating trend towards renewable-based power systems and the growing dependence of future electrical grids on variable renewable-energy resources. Moreover, the fast growth of renewable-energy penetration presents big operational challenges as renewable generation is intrinsically intermittent and uncertain. The output of solar PV is a function of irradiance and weather conditions, and wind generation is highly sensitive to atmospheric fluctuations. As renewable penetration increases, it becomes more difficult to maintain power balance, voltage regulation, frequency stability, and dependable energy delivery. Hence, the advanced energy-management strategies are needed for stable and efficient operation of smart-grid under dynamic operating conditions.

Among various renewable technologies, solar PV systems are widely adopted because of their low maintenance requirements and continuously decreasing installation costs. Wind-energy systems provide high power-generation capability under suitable atmospheric conditions, while hydroelectric systems offer relatively stable and reliable renewable-power output [4]. Biomass-energy systems are gaining attention due to their ability to convert agricultural and organic waste into useful electrical energy. Similarly, hydrogen fuel-cell systems are emerging as promising clean-energy technologies because of their high efficiency and near-zero-emission operation. Although these renewable sources provide several advantages, their large-scale integration into smart grids introduces major technical challenges related to intermittency, power fluctuations, voltage instability, frequency deviation, load-demand mismatch, energy-storage management, and power-quality degradation [5].

In recent years, several researchers have proposed mathematical-modeling and simulation-based techniques for evaluating renewable-energy systems. Conventional analytical approaches mainly focus on efficiency analysis, power-output estimation, capacity-factor calculation, reliability assessment, environmental-impact evaluation, and economic analysis of individual renewable sources. These methods are computationally simple and useful for preliminary renewable-energy assessment [6]. However, conventional approaches are generally unable to perform intelligent real-time coordination among multiple renewable sources under dynamic operating conditions. Furthermore, renewable sources such as solar PV and wind exhibit highly variable power generation due to changing irradiance and wind-speed conditions, which creates significant operational difficulties in maintaining smart-grid stability and reliable power delivery [7].To overcome these limitations, current research is increasingly focusing on Artificial Intelligence (AI) assisted energy-management systems for smart-grid applications. AI-based techniques such as intelligent forecasting, adaptive load balancing, predictive control, machine learning, and smart energy scheduling can significantly improve the utilization of renewable energy and the performance of the grid [8]. AI-driven smart-grid architectures enable dynamic coordination among renewable-energy sources, battery energy storage systems and interaction with the utility grid. These systems can intelligently predict the availability of renewable power, optimize battery charging and discharging operations, reduce power mismatch, improve voltage and frequency regulations, and enhance the overall grid reliability. Therefore, AI-assisted renewable-energy management is developing to be one of the most important research fields for next-generation sustainable power systems [9].

Motivated by these challenges and research opportunities, this paper presents a comparative performance analysis of two different renewable-energy assessment techniques: a conventional mathematical-modeling-based approach and an AI-assisted intelligent smart-grid energy-management framework. Initially, a detailed comparative analysis of major renewable-energy sources including solar PV, wind, hydro, biomass, and fuel-cell systems is performed using analytical and statistical methods [10]. Parameters such as mean power output, standard deviation, efficiency, reliability, installation cost, environmental impact, and capacity factor are evaluated under varying environmental conditions using MATLAB/Simulink 2024b. After analyzing the limitations of the conventional approach, an AI-assisted smart-grid energy-management system is developed to perform intelligent renewable coordination, adaptive power balancing, battery-energy storage management, and grid-support operation under real-time load-demand conditions [11].

The proposed AI-assisted framework incorporates renewable forecasting, adaptive dispatch control, battery state-of-charge management, smart grid import/export operation, and intelligent renewable scheduling to improve overall system performance. The developed system continuously monitors renewable generation and load demand to minimize power mismatch and maintain stable smart-grid operation [12]. In addition, voltage-stability indicators, frequency-response characteristics, renewable-utilization ratio, grid dependency, reliability index, and power-balancing performance are evaluated to compare the effectiveness of the conventional and AI-assisted approaches.

The major contributions of this research work are summarized as follows:

• Development of a comprehensive mathematical model for comparative analysis of solar PV, wind, hydro, biomass, and fuel-cell renewable-energy systems.

• Design of an AI-assisted smart-grid energy-management framework for intelligent renewable-power coordination and adaptive energy balancing.

• Integration of battery-energy storage and utility-grid support mechanisms for improved smart-grid operation and renewable utilization.

• Comparison of conventional renewable-energy estimation and AI-enabled energy-management strategies under different operating conditions.

• Evaluation of critical performance parameters of smart grid including power mismatch, voltage stability, frequency stability, reliability index, renewable-energy utilization and grid dependency.

• Development of a MATLAB/Simulink simulation platform for nextgeneration renewable smart-grid research and sustainable-energy applications.

Simulation results indicate that traditional mathematical approaches are effective for basic renewable-energy performance evaluation, but the AI-assisted smart-grid framework demonstrates better performance in smart load-demand matching, renewable-energy coordination, operational stability, and system reliability. The proposed work will provide useful insights to the researchers, engineers, and policy makers working in the fields of renewable-energy integration, smart-grid technology, intelligent energy management, and AI-enabled sustainable power systems.

2. Literature Review

The rapid growth of renewable-energy deployment and energy-storage technologies has significantly increased the need for intelligent energy management solutions. According to the International Renewable Energy Agency (IRENA), global renewable-energy capacity reached approximately 4,448 GW by the end of 2024, with around 585 GW added in a single year. The increasing penetration of intermittent renewable sources has created new challenges related to energy balancing, storage coordination, grid stability, and power-quality management, thereby making smart-grid energy management systems an important research area [13].

A significant recent contribution was presented by Uddin, Mo, and Dong, who proposed a real-time energy management framework for community microgrids based on Deep Reinforcement Learning (DRL) using the Proximal Policy Optimization (PPO) algorithm. Their study compared a conventional rule-based controller with a DRL-based controller in a hybrid PV–wind–battery–diesel–grid system. The proposed DRL-PPO approach achieved approximately 18% lower operational cost, 20% lower CO_2 emissions, 87.5% higher reliability, and 13% higher renewable-energy utilization compared with the conventional controller. These results demonstrate the effectiveness of AI-based decision-making in improving microgrid performance. However, the study was validated using a specific Australian community microgrid configuration and therefore requires further investigation for systems involving additional renewable sources such as hydropower, biomass, and fuel-cell technologies. Moreover, large-scale deployment and computational scalability were not extensively addressed [14].

Khanum et al. provided a comprehensive overview of the prospects and challenges associated with Artificial Intelligence-based Energy Management Systems for microgrids. Their review highlighted the importance of AI techniques in addressing renewable-generation forecasting, load prediction, power-flow optimization, cybersecurity, operational-cost reduction, and energy scheduling. The authors also discussed future research directions including self-healing microgrids, Internet of Things (IoT) integration, blockchain-enabled energy trading, explainable AI, privacy protection, and scalability enhancement. Although the review provides a valuable roadmap for future research, it remains primarily conceptual and does not present a complete implementation framework capable of coordinating multiple renewable resources, battery storage, and grid interaction within a unified smart-grid architecture [15].

A comprehensive review by Talaat et al. investigated the application of Artificial Intelligence techniques for the integration and management of hybrid renewable-energy microgrids. The authors examined various AI approaches, including Artificial Neural Networks (ANN), Fuzzy Logic, Genetic Algorithms, Particle Swarm Optimization (PSO), and Machine Learning techniques for forecasting, optimization, and control applications. Their findings demonstrated that AI-based approaches can significantly improve prediction accuracy, operational efficiency, and renewable-energy utilization. The review further highlighted the challenges associated with renewable intermittency, communication infrastructure, and control-system complexity. However, the study primarily focused on reviewing existing technologies and did not provide a fully integrated real-time EMS framework capable of simultaneously managing renewable coordination, battery scheduling, and smart-grid stability [16].

Amiri et al. proposed an explainable Deep Reinforcement Learning framework for resilient microgrid energy management under extreme weather conditions. The study integrated PPO with Local Interpretable Model-Agnostic Explanations (LIME) to improve transparency in AI-based decision-making. The proposed framework achieved a resilience index of 0.9736 and an estimated battery lifetime of 15.11 years in a renewable-energy-based microgrid subjected to cyclone disturbances. The study demonstrated the potential of explainable AI in enhancing trust and reliability in critical energy systems. Nevertheless, the investigation was limited to a specific wind–solar–battery configuration and extreme-weather scenario. Therefore, its applicability to broader hybrid renewable-energy systems involving multiple dispatchable sources remains to be validated [17].

From the control-system perspective, Model Predictive Control (MPC) has emerged as one of the most widely investigated approaches for microgrid energy management. Existing MPC-based studies have demonstrated effective power balancing, renewable-energy coordination, and economic optimization through predictive decision-making. The ability of MPC to forecast future operating conditions enables proactive management of renewable intermittency and load variations. However, several researchers have reported that MPC-based controllers suffer from high computational complexity, extensive model requirements, and increased processing burden for large-scale systems. These limitations can restrict real-time implementation, particularly in smart-grid environments containing multiple renewable-energy resources and storage units. Consequently, AI-assisted control strategies are increasingly being explored as alternatives capable of achieving adaptive operation with reduced computational requirements [18].

Energy-storage planning has also received significant attention in renewable-energy research. Psarros and Papathanassiou demonstrated that appropriately sized storage systems can substantially reduce renewable-energy curtailment and overall generation costs in high-renewable power systems. Their analysis indicated that an optimal combination of battery storage and pumped-hydro storage can improve system flexibility and renewable-energy utilization. Although the study successfully addressed storage planning and economic optimization, it did not consider AI-driven real-time energy management, adaptive battery scheduling, renewable forecasting, or intelligent source coordination. Therefore, additional research is required to integrate storage planning with intelligent operational control strategies [19].

Recent studies have further emphasized the role of Artificial Intelligence in improving microgrid reliability, forecasting accuracy, fault diagnosis, and renewable-energy management. AI-based optimization techniques have shown considerable potential in enhancing system resilience and power quality under varying operating conditions. Despite these advancements, most existing studies focus either on forecasting, optimization, storage planning, or control strategies individually. Limited research has been reported on a unified framework that simultaneously integrates multiple renewable-energy sources, battery energy storage, intelligent energy management, bidirectional grid interaction, and stability enhancement within a single smart-grid environment. This research gap motivates the development of the proposed AI-assisted smart-grid energy management framework presented in this work.

In table no. 1summary of recent literature on AI-assisted energy management systems. The recent literature demonstrates significant advancements in AI-assisted energy management, renewable energy integration, battery optimization, and smart-grid control. However, several challenges remain regarding unified system coordination, real-time intelligent decision-making, scalability, and comprehensive energy optimization.

Table No. 1. Summary of Recent Literature on AI-Assisted Energy Management Systems.

Ref.	Authors	Method/Technique	Major Contribution	Limitations
[13]	IRENA	Global Renewable Energy Statistics	Reported 4,448 GW renewable capacity by end of 2024 with 585 GW added; highlights need for intelligent EMS.	Statistical report only; no EMS framework.
[14]	Uddin et al.	DRL (PPO)	18% lower cost, 20% lower CO_2, 87.5% higher reliability, 13% higher renewable utilization.	Specific Australian microgrid; scalability not addressed.
[15]	Khanum et al.	AI-EMS Review	Reviewed AI for forecasting, scheduling, cybersecurity.	No unified implementation.
[16]	Talaat et al.	ANN, FL, GA, PSO, ML	Reviewed AI for forecasting, optimization and control.	No integrated real-time EMS.
[17]	Amiri et al.	Explainable DRL (PPO+LIME)	Improved resilience and battery lifetime.	Limited renewable configuration.
[18]	Various Researchers	MPC	Effective predictive energy management.	High computational complexity.
[19]	Psarros & Papathanassiou	Storage Planning	Reduced curtailment and generation cost.	No AI real-time EMS.

3.METHODOLOGY

3.1 System Modeling and Problem Formulation

The proposed research develops an AI-assisted smart-grid renewable energy management framework for comparative analysis and intelligent coordination of multiple renewable energy sources. The system integrates solar photovoltaic (PV), wind, hydro, biomass, and fuel-cell generation with battery energy storage and utility-grid support. The complete model is implemented in MATLAB to analyze renewable-energy variability, smart-grid power balancing, storage coordination, voltage stability, and frequency response under varying environmental and load conditions.

The smart-grid architecture consists of renewable-energy generation units, a battery energy storage system (BESS), an intelligent energy management system (EMS), and a bidirectional utility-grid interface. Renewable sources generate power according to continuously changing environmental conditions such as solar irradiance, temperature, wind speed, water-flow variation, biomass-fuel availability, and hydrogen supply. Since renewable sources are inherently intermittent and uncertain, intelligent coordination is required to maintain stable and reliable grid operation.

The proposed methodology is divided into two major stages:

1. Conventional renewable-energy comparative analysis
2. AI-assisted smart-grid energy management and coordination

The first stage evaluates renewable sources individually using conventional analytical and statistical methods, while the second stage introduces intelligent energy management for adaptive renewable coordination and smart-grid stabilization [20].

3.1.1 Solar Photovoltaic (PV) System Modeling

The solar photovoltaic system is modeled using irradiance-dependent and temperature-dependent characteristics to represent realistic solar-power generation behavior. Solar irradiance varies continuously throughout the day, producing low generation during morning and evening hours and maximum generation during midday conditions.

The PV output power is expressed as:

$$P_{PV} = P_{rated}\left(\frac{G}{1000}\right)\left(\frac{\eta_{PV}}{\eta_{ref}}\right) \quad (1)$$

where:

- P_{PV}= PV output power

- P_{rated}= Rated PV power
- G= Solar irradiance (W/m^2)
- η_{PV}= Temperature-dependent PV efficiency
- η_{ref}= Reference PV efficiency

The PV efficiency decreases with increasing temperature because higher cell temperature reduces semiconductor conversion efficiency. Therefore, even under high irradiance conditions, excessive temperature slightly lowers PV output power.

The PV model in the proposed work captures realistic daily solar behavior, including sunrise generation increase, peak midday generation, and evening power reduction [21].

3.1.2 Wind Energy System Modeling

The wind-energy conversion system is modeled using a practical wind-turbine power curve containing cut-in speed, rated speed, and cut-out speed regions. The wind speed is randomly varied during the simulation time to account for realistic atmospheric fluctuations and turbulence.

The wind-turbine output power is expressed as

$$P_{wind} = P_{rated}\left(\frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3}\right) \quad (2)$$

Where:

- P_{wind}= Wind-turbine output power
- v= Wind speed
- v_{ci}= Cut-in wind speed
- v_r= Rated wind speed

If wind speeds are below the cut-in speed the turbine will not produce power. Between cut-in and rated speed, power rises rapidly according to the cubic wind-speed relationship.

The output is approximately constant above rated speed until cut-out speed is reached.

This model is well suited to describe the intermittent and highly fluctuating nature of wind energy, which creates problems for the stability and power balance of smart grids [22].

3.1.3. Modeling of Hydro Power System

The hydro-power system is modelled as a semi-dispatchable renewable source depending on the water-flow availability and turbine efficiency. Hydro generation is a smoother, more stable output than solar and wind systems because time variations in water-flow are gradual.

The hydro-power output is given by:

$P_{hydro} = \eta \rho g Q H$(3)

where:

- P_{hydro}= Hydro output power
- η= Turbine-generator efficiency
- ρ= Water density
- g= Gravitational acceleration
- Q= Water-flow rate
- H= Hydraulic head

Hydro generation provides important support for balancing renewable intermittency because its output can be partially controlled according to system demand [23].

3.1.4. Modelling of biomass energy system

The biomass-energy system is modeled as a controllable renewable source, the operation of which is driven by the availability of biomass-fuel. Biomass generation is relatively stable compared with solar and wind systems, because biomass fuel can be stored and continuously supplied.

The biomass output power is expressed as: (

P_biomass = P_rated * Fuel_availability (4)

where;

biomass power output P_biomass=Fuel_availability= Biomass fuel availability factor

The biomass generation provides a dispatchable renewable source and helps the smart grid in the case of renewable deficit conditions [24].

3.1.5. Modeling of the fuel cell system

The fuel cell system is modeled based on hydrogen availability and electrochemical conversion characteristics . Because the supply of hydrogen can be controlled, fuel cells can provide a smoother and more controllable output than highly intermittent renewables.

The fuel-cell output is expressed as:

$P_{FC} = P_{rated} \times H_2Availability$ (5)

where:

- P_{FC}= Fuel-cell output power
- $H_2Availability$= Hydrogen availability factor

Fuel cells improve renewable-energy reliability and support voltage and frequency stabilization during sudden renewable fluctuations [25].

3.1.6. Smart-Grid Load Modeling

A realistic smart-grid load profile is developed to capture the time-varying electricity demand of residential, commercial, and community consumers. The load model takes into account the typical daily consumption characteristics, including low load during late-night hours, a gradual increase during the morning period, moderate fluctuations throughout the day, and a high peak during the evening hours caused by increased consumer activity. Random load variations are imposed to mimic real operating conditions, capturing the effects of appliance switching, consumer-behavior variations, and stochastic demand uncertainty.

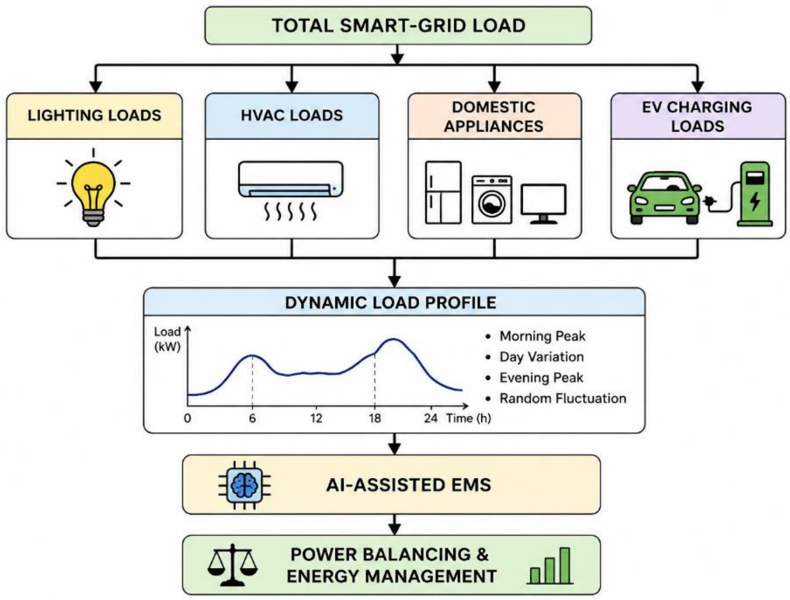

Fig. 3. Dynamic load modeling for AI-assisted smart-grid operation.

Fig. 3 illustrates the proposed smart-grid load modeling framework, where different consumer loads are aggregated to generate a dynamic load profile characterized by daily demand variations and random fluctuations. The generated load information is utilized by the AI-assisted EMS for forecasting, power balancing, battery coordination, and intelligent energy management.

The load demand is modeled by a dynamic time-dependent profile that varies continuously throughout the 24-hour operating period. These variations create realistic power-balancing challenges for renewable-energy coordination, battery scheduling, and utility-grid interaction. Since renewable-energy generation and consumer demand rarely match perfectly, the developed load model provides a realistic platform for evaluating the proposed AI-assisted EMS under dynamic operating conditions. The model supports forecasting, power-mismatch prediction, battery coordination, and grid interaction, enabling assessment of renewable-energy utilization, system reliability, voltage stability, and frequency regulation [26].

3.1.7. Conventional Renewable-Energy Comparative Analysis

The first phase of the study is about a standard mathematical and statistical comparison of renewable energy technologies. Each renewable source is analyzed separately, without intelligent coordination or storage support.

The comparative analysis considers several key technical and operational parameters such as mean power output, standard deviation, efficiency, capacity factor, reliability index, installation cost and environmental impact score. Together, these parameters provide a broad guideline for assessing and comparing different systems/technologies on the basis of their performance, stability, economic viability and environmental sustainability. Average power output of renewables is calculated by:

$$\bar{P} = \frac{1}{N}\sum_{i=1}^{N} P_i \quad (6)$$

where:

- $\bar{P}$= Mean power output
- P_i= Instantaneous power samples
- N= Number of observations

The output-power fluctuation is measured using standard deviation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - \bar{P})^2} \quad (7)$$

This stage provides the baseline renewable-performance evaluation and highlights the intermittency problems associated with standalone renewable systems [26].

3.1.8. AI Assisted Energy Management System (EMS)

The second phase of the suggested methodology suggests an AI aided intelligent energy management system for renewable coordination and adaptive power balancing.The EMS employs forecast-like signals of renewable generation and load demand for intelligent supervisory control. The controller continuously predicts renewable mismatch conditions and dynamically schedules dispatchable renewable sources according to battery SOC and system demand.The AI-assisted control strategy uses a set priority order to achieve optimal energy management and system stability. First, it gives priority to renewable energy sources that are "must-take," such as solar photovoltaic (PV) and wind power. It then adaptively schedules controllable generation sources including hydro, biomass and fuel-cell power in accordance with demand and availability. Then it manages the charging and discharging of battery storage systems to smooth out fluctuations in supply and demand. Finally, where necessary, the system makes possible power exchange with the utility grid, ensuring reliability and guaranteeing continuous power supply. The smart EMS improves the usage of renewable energy, decreases the fluctuation of the power, improves the stability of the grid and reduces unnecessary dependence on the grid [27].

3.1.9. Battery Energy Storage System (BESS)

Integration of battery energy storage system in the smart grid framework for mitigating renewable intermittency and improving energy balancing.

The battery is used in three major operating conditions:

Early Morning Operations

• At times of low solar generation, renewable generation cannot meet the load demand. Thus, the battery provides power to the grid and the SOC decreases.

Midday Charge Operation

• midday solar generation rises, renewable power above load demand. The surplus renewable energy is used to charge the battery and the SOC is continuously increasing.

• Afterwards, SOC is kept nearly constant at a safer operating value to preserve battery health and reserve energy availability by the EMS.

Evening and Night Operation

During evening and nighttime conditions, solar generation decreases rapidly. The battery again discharges to support load demand and maintain grid stability, causing SOC reduction. The battery SOC during discharge is calculated as:

$$SOC(k+1) = SOC(k) - \frac{P_{bat}\Delta t}{\eta_{dis} E_{max}} \quad (8)$$

For charging operation:

$$SOC(k+1) = SOC(k) + \frac{|P_{bat}|\Delta t \eta_{ch}}{E_{max}} \quad (9)$$

where:

- SOC= State of charge
- P_{bat}= Battery power
- E_{max}= Maximum battery energy capacity
- η_{ch}= Charging efficiency
- η_{dis}= Discharging efficiency
- Δt= Sampling interval [28]

3.2. Grid Interaction and Power Balancing

The utility grid serves as backup support source in renewable deficit conditions and absorbs excess renewable energy in surplus conditions.

Bidirectional interaction with the grid promotes use of renewable energy and avoids unnecessary curtailment of renewables.

The real-time power balance equation is formulated as:

$$P_{generation} + P_{grid} = P_{load} + P_{loss} \quad (10)$$

where:

- $P_{generation}$= Total renewable and battery generation
- P_{grid}= Grid import/export power
- P_{load}= Smart-grid load demand
- P_{loss}= System losses

This equation ensures continuous supply-demand balancing throughout the simulation period and maintains stable smart-grid operation under varying renewable-energy conditions [29].

4. Forecasting and Intelligent Decision-Making Framework

The proposed AI-assisted energy management framework combines forecasting and intelligent control to improve renewable-energy coordination within the smart grid. The following sections present the renewable and load forecasting models, power-mismatch prediction mechanism, intelligent dispatch strategy, and adaptive battery coordination approach that collectively support reliable, efficient, and stable system operation.

4.1 Forecast-Based Smart-Grid Operation

Fig. 2 illustrates the proposed forecasting and intelligent decision-making framework used in the AI-assisted smart-grid energy management system (EMS). The framework integrates renewable-energy forecasting, load-demand prediction, power-mismatch estimation, intelligent dispatch control, battery coordination, and grid interaction in a unified supervisory architecture.

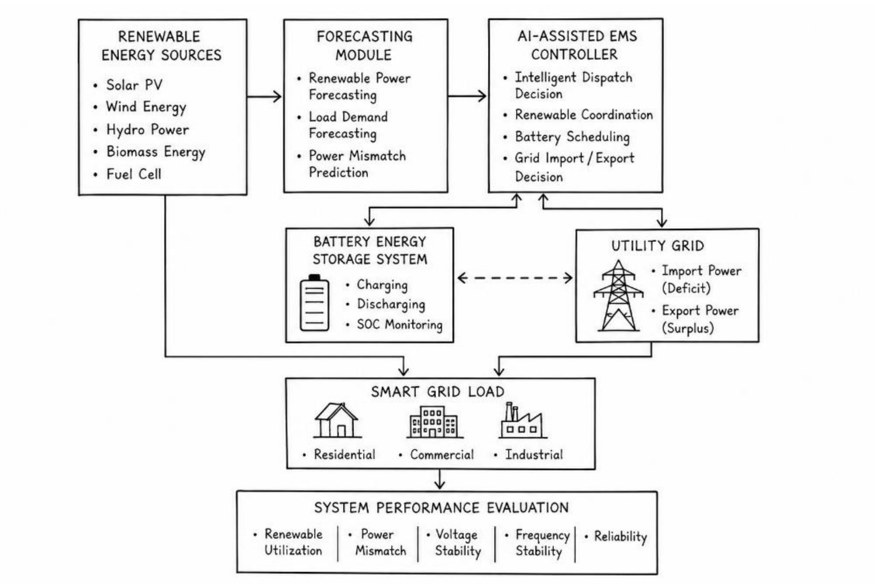

Fig.2 Proposed AI-Assisted Forecasting and Intelligent Decision-Making Framework for Smart-Grid Energy Management.

Initially, real-time data from renewable-energy sources including solar PV, wind, hydro, biomass, and fuel-cell systems are continuously collected. Simultaneously, smart-grid load demand is monitored under varying consumer conditions. These measured signals are then provided to the forecasting layer, where forecast-like renewable and load signals are generated to represent practical prediction behavior under uncertain environmental conditions.

Conceptually, the forecasting layer acts as the intelligent "brain" of the smart-grid controller because it predicts future operating conditions before actual imbalance occurs [30].

4.2 Renewable Power Forecasting

Forecast signals are generated for all renewable-energy sources including solar PV, wind, hydro, biomass, and fuel-cell systems. The forecasted renewable power is obtained by adding practical uncertainty to the actual renewable-generation profile in order to simulate realistic prediction behavior.The forecasting equation is expressed as:

$$P_{forecast} = P_{actual} + Noise \quad (11)$$

where:

- $P_{forecast}$= Forecasted renewable power
- P_{actual}= Actual renewable power
- $Noise$= Forecasting uncertainty or prediction error

This forecasting layer helps the EMS estimate future renewable availability under varying environmental conditions [31].

4.3 Load-Demand Forecasting

A forecasted smart-grid load profile is developed to estimate future consumer demand. The load model includes morning demand rise, daytime variation, evening peak demand, and random load uncertainty.

The load-forecast equation is given as:

$$P_{load,f} = P_{load} + Noise \quad (12)$$

where:

- $P_{load,f}$= Forecasted load demand
- P_{load}= Actual load demand
- $Noise$= Consumer-demand uncertainty

The predicted load profile enables proactive scheduling of renewable resources before actual demand fluctuation occurs [32].

4.4 Power-Mismatch Prediction

The AI-assisted EMS continuously predicts future renewable-generation mismatch using forecasted renewable and load signals.

The mismatch equation is expressed as:

$P_{mismatch} = P_{load,f} - P_{ren,f}$(13)

where:

- $P_{mismatch}$ = Forecasted power mismatch
- $P_{load,f}$ = Forecasted load demand
- $P_{ren,f}$ = Forecasted renewable generation

If: $P_{mismatch} > 0$(14)

the system predicts an energy-deficit condition.

If: $P_{mismatch} < 0$(15)

the system predicts excess renewable generation.

This predicted mismatch forms the basis of intelligent renewable coordination and battery scheduling [33].

4.5 Intelligent Dispatch Decision Logic

Based on the predicted mismatch condition, the EMS dynamically adjusts dispatchable renewable sources such as hydro, biomass, and fuel-cell systems.

The preliminary renewable-generation equation is expressed as:

$P_{gen} = P_{pv} + P_{wind} + P_{hydro} + P_{biomass} + P_{fc}$ (16)

where:

- P_{pv} = Solar PV power
- P_{wind} = Wind power
- P_{hydro} = Hydro power
- $P_{biomass}$ = Biomass power
- P_{fc} = Fuel-cell power

In case of increasing forecasted deficit the participation of hydro, biomass and fuel cell is increased adaptively. When there is a renewable excess, priority is to charge batteries and export to the grid.

The EMS acts as an intelligent operator that continuously balances the availability of renewables with the load demand [34].

4.6 Coordinated Adaptive Battery Scheme

The EMS always monitors the battery State of Charge (SOC) and takes smart charging/discharging decisions based on availability of renewables and load condition.

Figure 3 illustrates the adaptive battery management strategy and the corresponding SOC behavior over a 24-hour operating cycle. The battery discharges during early morning and night to compensate the renewable power deficits, while the excess renewable energy during daytime is used for battery charging. A stable SOC region is maintained during peak renewable generation to preserve reserve energy and improve battery life. The proposed strategy enables efficient energy storage utilization and supports stable smart-grid operation under varying renewable and load conditions.

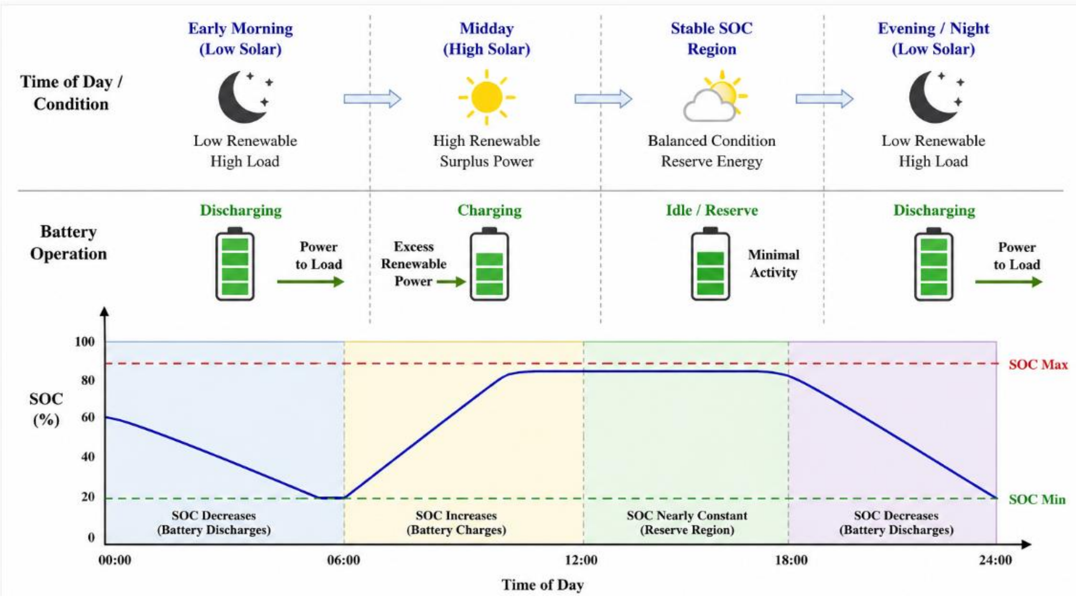

Fig.3 AI-assisted adaptive battery coordination strategy and SOC evolution over a 24-hour operating cycle.

4.6.1 Early Morning Operation

During low-solar conditions, the battery discharges to support load demand, causing SOC reduction.

Battery-discharge equation:

$$SOC(k+1) = SOC(k) - \frac{P_{bat}\Delta t}{\eta_{dis} E_{max}} \quad (17)$$

where:

- $SOC(k)$= Present battery state of charge
- $SOC(k+1)$= Updated battery state of charge

- P_{bat}= Battery discharge power
- Δt= Sampling interval
- η_{dis}= Battery discharge efficiency
- E_{max}= Maximum battery energy capacity

4.6.2 Midday Charging Operation

During peak solar-generation hours, excess renewable power charges the battery and SOC increases.

Battery-charging equation:

$$SOC(k+1) = SOC(k) + \frac{|P_{bat}|\Delta t\,\eta_{ch}}{E_{max}} \quad (18)$$

where:

- η_{ch}= Battery charging efficiency

The SOC gradually rises toward a safer operating region.

4.6.3 Stable SOC Region

After reaching a safer SOC value, battery charging/discharging activity is minimized and SOC remains nearly constant for reserve-energy availability.

This operating region improves battery life and system reliability.

4.6.4 Evening/Night Operation

During evening and nighttime conditions, solar generation decreases significantly. The battery again discharges to support the smart-grid load, causing SOC reduction.

This adaptive SOC-management strategy reduces renewable intermittency and improves smart-grid stability [35-36].

4.7 Intelligent Grid Interaction

The EMS performs bidirectional utility-grid interaction according to renewable-generation and load conditions.

Renewable Deficit Condition

When renewable generation and battery support are insufficient:

$$P_{grid\_import} > 0 \quad (19)$$

The utility grid supplies additional power to maintain load balance. In this condition, the EMS continuously monitors the power deficit and imports the required electricity from the utility grid to ensure uninterrupted power supply to consumers. Grid import prevents load shedding, maintains voltage and frequency stability, and guarantees reliable operation of the smart-grid system during periods of low renewable-energy availability.

Renewable Surplus Condition

When renewable generation exceeds the load demand:

$P_{grid\_export} > 0$(20)

Excess renewable power is exported to the utility grid. In this condition, the EMS exports excess energy of solar and wind to the utility grid after fulfilling the local load demand and battery charging requirements. This exported energy can be used by other consumers connected to the grid, reducing renewable-energy curtailment, improving energy utilization, and creating additional value from clean-energy resources.

The power-balance equation in real-time is written as:

P_gen+P_grid=P_load+P_loss(21)

Where, Pgrid is the imported power during deficit conditions and exported power during surplus conditions. The intelligent grid interaction results in the reduction of the waste of renewable energy, improvement of the capability of energy sharing between microgrid and utility grid, enhancement of the grid flexibility and increase of the overall efficiency of smart-grid operation [37].

4.8 Real-Time Supervisory Control

The proposed AI assisted Energy Management System (EMS) works continuously in real time in a sequential process to ensure efficient and reliable power management. It first assesses the current state of the system by measuring renewable generation and load demand. It forecasts the future trends with the availability of renewable energy and load conditions. Using these predictions, the system estimates the possible power mismatches and schedules the dispatchable renewable energy sources. Then it manages the charge and discharge of the battery storage systems to keep the balance of supply and demand. It is able to import or export the grid as required to maintain system stability and continuity of supply.

Finally, it continuously updates key performance indicators related to voltage and frequency stability to monitor and maintain overall power quality.

• The real-time supervisory framework enhances overall system performance by improving renewable energy utilization, strengthening power balancing capability, and ensuring better voltage stability. It also contributes to more effective frequency regulation and significantly increases the reliability of the smart grid. [38]

6.6 Comparative Analysis of Conventional and AI-Assisted Techniques

The comparative results clearly demonstrate the superiority of the proposed AI-assisted EMS over the conventional mathematical approach. While the conventional technique focuses primarily on renewable power generation modeling, it lacks intelligent decision-making capability and adaptive resource coordination. Consequently, energy storage utilization, grid interaction, and renewable energy management remain limited.

The AI-assisted framework introduces predictive and adaptive control, enabling coordinated operation of renewable resources, battery storage, and utility-grid support. The battery SOC is maintained within safe operating limits, renewable energy utilization is improved, grid dependency is reduced, and overall system stability is enhanced. Therefore, the proposed AI-assisted EMS provides a more efficient, reliable, and practical solution for modern renewable-energy-integrated smart-grid applications [39].

In tableno. 2 Comparison Between Conventional and AI-Assisted Energy Management Techniques. The performance of the proposed AI-assisted energy management framework is evaluated by comparing it with conventional energy management techniques across various operational parameters. As shown in Table 2, the proposed framework provides significant improvements in renewable energy utilization, battery optimization, grid stability, and overall system reliability, making it well suited for next-generation smart grid applications.

Table 2: Comparison Between Conventional and AI-Assisted Energy Management Techniques.

Performance Parameter	Conventional Technique	Proposed AI-Assisted EMS	Improvement Achieved
Renewable Source Operation	Independent operation of PV, Wind, Hydro, Biomass and Fuel Cell	Coordinated and adaptive operation of all renewable sources	Improved energy coordination
Decision Making Capability	Rule-based mathematical model	Intelligent forecasting and adaptive control	Predictive energy management
Load Matching	Limited load-generation matching	Dynamic load-generation balancing	Reduced power mismatch
Battery Management	Fixed charging/discharging strategy	Intelligent SOC-based charging/discharging	Improved battery utilization
Battery SOC Behavior	No optimized SOC control	SOC maintained between 20–90% operating range	Enhanced battery life and

			efficiency
Renewable Energy Utilization	Moderate utilization	Maximum utilization through coordinated dispatch	Higher renewable penetration
Renewable Curtailment	Higher during surplus periods	Reduced through battery charging and grid export	Lower energy wastage
Grid Import Dependency	High during renewable deficit	Reduced through intelligent storage utilization	Lower grid dependency
Grid Export Capability	Limited or uncontrolled	Controlled export during renewable surplus	Improved energy flexibility
Energy Storage Utilization	Partial utilization	Full utilization according to system requirements	Better storage performance
Power Balancing	Reactive balancing	Predictive and adaptive balancing	Improved operational efficiency
Voltage Stability	Susceptible to renewable fluctuations	Maintained close to 1.0 pu	Improved voltage regulation
Frequency Stability	Larger frequency variations	Maintained near 50 Hz	Improved frequency regulation
System Reliability	Moderate	High due to coordinated operation	Improved reliability
Power Quality	Dependent on source fluctuations	Improved through intelligent control	Better power quality
Operational Flexibility	Limited	High	Enhanced system adaptability
Smart Grid Compatibility	Limited	Fully compatible	Suitable for future smart grids
Overall System Performance	Conventional operation	Intelligent and optimized operation	Significant performance enhancement

5. Implementation

5.1 Simulation Environment

The proposed AI-assisted smart-grid energy management framework is implemented in MATLAB R2024b using a 24-hour simulation horizon with a one-minute sampling interval. The model integrates renewable-energy sources, battery energy storage, utility-grid interaction, and an intelligent energy management system (EMS) to evaluate smart-grid performance under dynamic operating conditions.

5.2 Simulation Parameters

The renewable-energy system consists of a 100 kW solar PV system, 120 kW wind turbine, 130 kW hydro unit, 90 kW biomass plant, and 60 kW fuel-cell system. A 300 kWh battery energy storage system is incorporated with maximum charging and discharging limits of 80 kW. Battery SOC is maintained between 20% and 90%, while utility-grid import and export limits are set to 120 kW and 80 kW, respectively [40].

5.3 Renewable Source Input Profiles

Realistic environmental profiles are generated to model renewable-energy variability. Solar irradiance and temperature are varied throughout the day to simulate PV generation. Wind speed is modeled using stochastic fluctuations, while hydro generation depends on water-flow availability. Biomass and fuel-cell outputs are determined according to fuel availability and hydrogen-supply conditions. These profiles enable realistic assessment of renewable intermittency and smart-grid operation.

5.4 AI-Assisted EMS Implementation

The EMS continuously monitors renewable generation, battery SOC, and load demand. Forecast-like renewable and load signals are generated to estimate future power mismatch. Based on predicted operating conditions, the EMS adaptively schedules hydro, biomass, and fuel-cell generation, controls battery charging/discharging, and performs grid-import/export operations. The control strategy prioritizes renewable-energy utilization while maintaining system stability and reducing grid dependency [41].

5.5 Simulation Flowchart

The overall simulation procedure adopted in this study is illustrated in Fig. 5.1. The process starts with environmental-condition and load-data generation, followed by renewable-power modeling for solar PV, wind, hydro, biomass, and fuel-cell sources. Subsequently, the AI-assisted EMS performs renewable/load forecasting, power-mismatch prediction, intelligent dispatch scheduling, battery SOC coordination, and utility-grid interaction. Finally, system performance is evaluated in terms of renewable-energy utilization, power balancing, battery behavior, voltage stability, frequency regulation, and grid dependency to validate the effectiveness of the proposed smart-grid framework

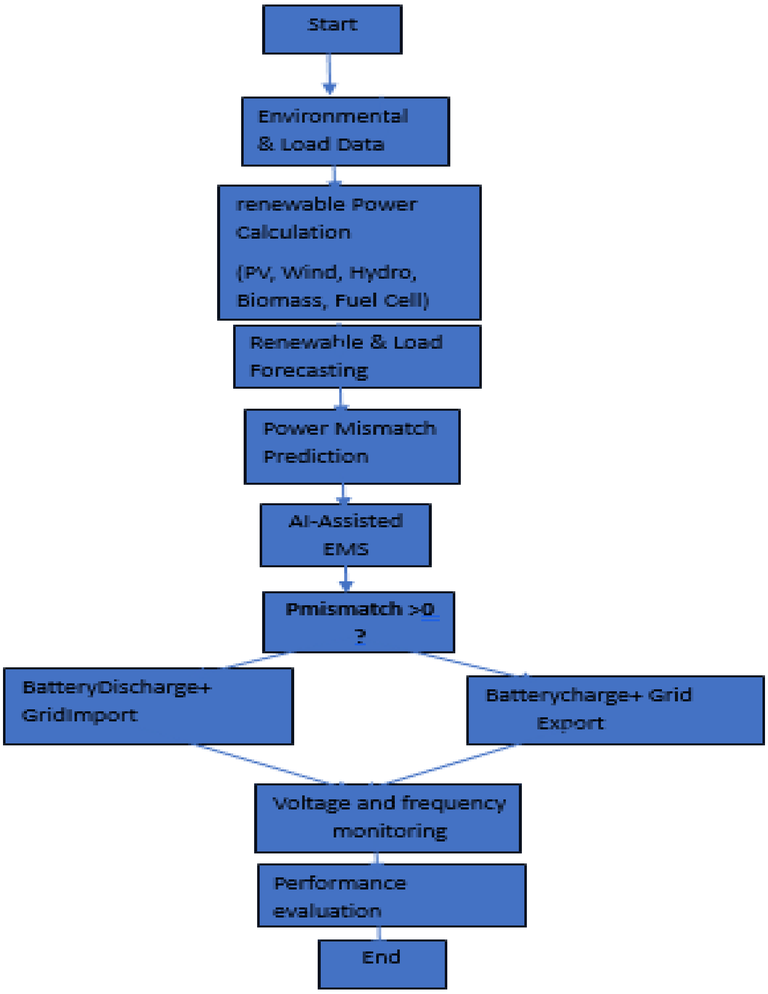

Fig. 5.5. Overall simulation flowchart of the proposed AI-assisted smart-grid energy management framework.

6. RESULT AND DISCUSSION

The following results present a comprehensive evaluation of the proposed AI-assisted smart-grid energy management system. The analysis includes renewable power output and energy coordination, battery energy storage performance, grid interaction and power balancing, renewable-energy utilization, and voltage-frequency stability assessment. A comparative investigation of conventional and AI-assisted operation is also carried out to demonstrate the effectiveness of intelligent energy management in enhancing renewable utilization, operational reliability, and overall smart-grid performance.

6.1 Renewable Power Output and Energy Coordination

The conventional renewable energy model employs pre-established mathematical expressions to characterize the operational features of solar PV, wind, hydro, biomass, and fuel-cell sources . The resulting power profiles show that the solar PV generation follows a typical pattern, depending on the irradiance, reaching a maximum of about 97 kW around noon, and zero generation during the night. Wind power exhibits considerable fluctuations throughout the day, ranging from approximately 15 kW to 65 kW, dependent on the wind speed conditions. On the other hand, hydro, biomass and fuel-cell sources have relatively stable power generation. Hydro has an output between 76 kW and 85 kW, biomass operates around 70-75 kW and the fuel-cell source has a nearly constant power of 34-37 kW . These generation characteristics can be observed in Result 6.1, where the intermittent nature of solar and wind resources is evident when compared with the stable behavior of hydro, biomass, and fuel-cell systems.

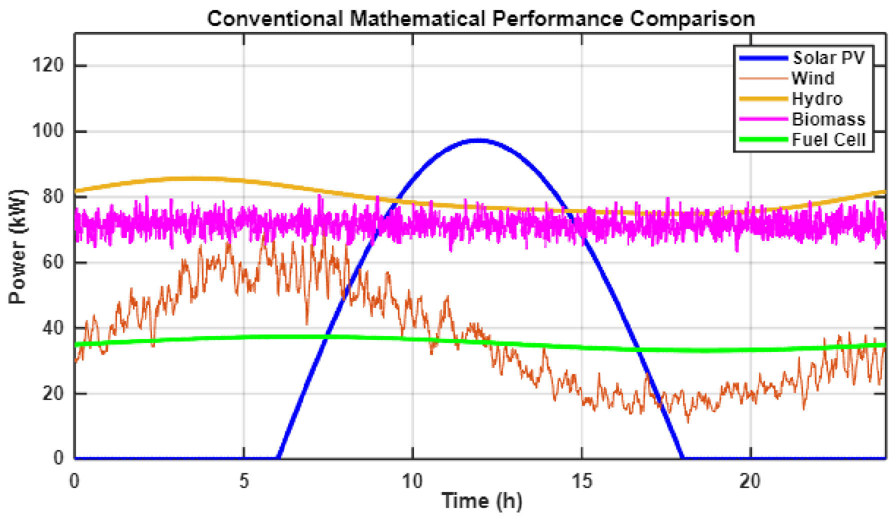

Fig. 6.1 Conventional renewable source power output profiles over a 24-hour period.

The traditional model can simulate the individual behavior of renewable energy sources, but it does not have an intelligent mechanism for the coordinated allocation of energy between available resources. A composite performance assessment of each source was performed as a further evaluation of the effectiveness of each source. The related ranking results show that hydro had the highest composite score of about 0.89, followed by biomass with 0.66, fuel cell with 0.46 and wind with 0.44 while solar PV had the lowest score of about 0.20 due to its intermittent operating characteristics. These comparative results are summarized in Result 6.2 which clearly shows the better reliability and consistency of hydro and biomass sources compared to solar PV and wind generation.

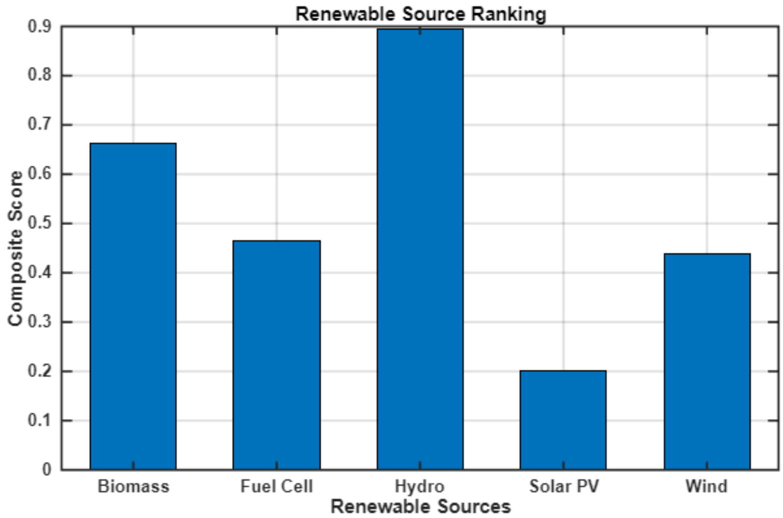

Figure 6.2. Composite performance ranking of renewable energy sources.

Based on this observation, the proposed AI-assisted Energy Management System (EMS) utilizes source performance information, load demand, battery state-of-charge, and grid requirements to achieve intelligent energy coordination. The EMS improves the utilization of renewable energy, the system reliability, and the power distribution balance in the microgrid by dynamically prioritizing the available renewable resources based on their operational conditions and performance rankings. Hence, the proposed approach can achieve much better renewable energy coordination and operational efficiency than the traditional renewable energy management model.

6.2 Battery Energy Storage Performance

The battery SOC profile represents the performance of the proposed AI-assisted EMS.Initially, the battery SOC decreases from approximately 60% to 20% during the early morning period due to insufficient renewable generation and the need to support load demand. The battery is in discharge mode during this time to keep the system power balanced. In the morning as solar generation becomes available, the battery begins charging with the excess renewable energy. The SOC increases rapidly from 20% to around 90% between the hours of 07:00 h and 11:00 h, indicating the surplus renewable energy is being effectively utilized. The SOC during midday operation is almost constant around 90%, which means enough energy has been stored while the load demand is sufficiently satisfied by the renewable generation. Fig. 6.1 clearly shows the characteristics of battery charging, discharging and SOC.

.

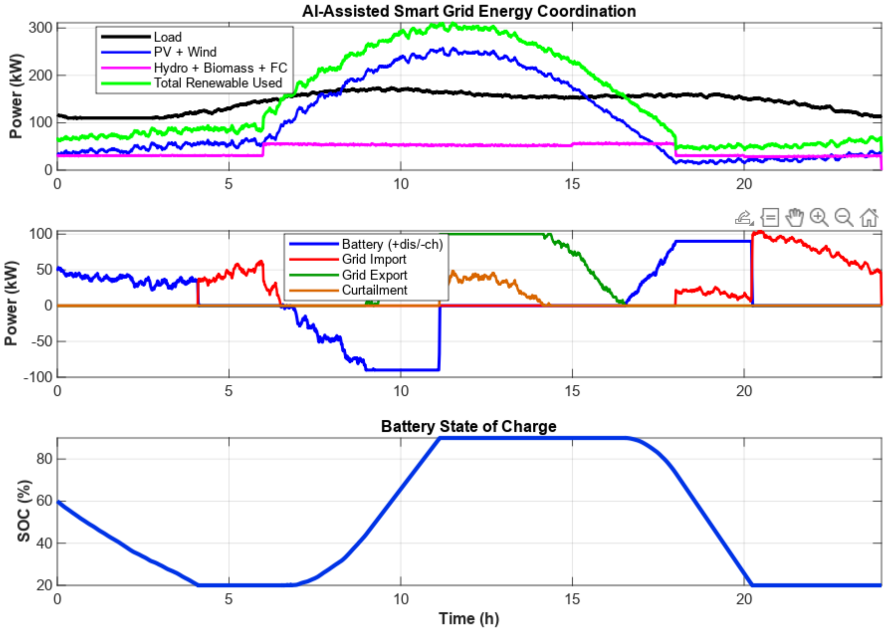

Fig. 6.1: Coordinated operation of renewable sources, battery storage, and grid interaction.

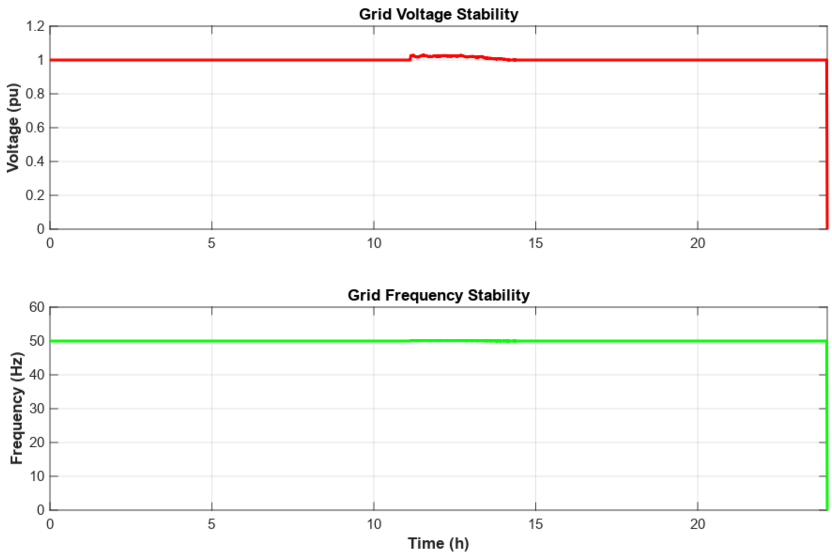

Fig. 6.2: Voltage and frequency stability under AI-assisted EMS operation.

During evening and nighttime periods, the battery discharges again to compensate for reduced solar generation, resulting in a gradual decline in SOC. This coordinated battery operation contributes to maintaining stable system voltage and frequency throughout the day, as illustrated in Fig. 6.2. Furthermore, the high renewable energy utilization and reliability performance achieved through effective battery management are reflected in the performance indicators presented in Fig. 6.3. Therefore, the proposed AI-assisted EMS significantly improves battery utilization and energy storage management compared with conventional approaches.

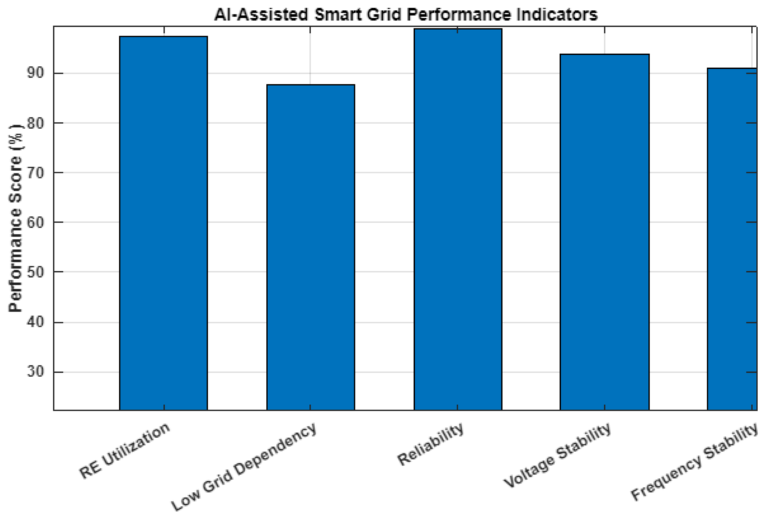

Fig. 6.3: Performance evaluation of the proposed AI-assisted smart grid.

6.3 Grid Interaction and Power Balancing

The proposed EMS keeps the continuous power balance through intelligent coordination of renewable energy sources, battery storage and utility grid support. During early morning and late evening periods renewable generation is not enough to meet load demand. In such cases, the import of power from the grid is controlled to guarantee a reliable power supply. The maximum grid import during the simulation is in the range of 100 kW. The grid import/export behavior and the overall power-balancing operation are shown in Fig. 6.1. By midday, there is more renewable generation, with the renewable power available exceeding both the load demand and the need for battery charging. Excess renewable energy is exported to the utility grid. The maximum export is almost 100 kW.This ability to exchange power in both directions increases operational flexibility and reduces unnecessary dependence on utility support. As illustrated in Fig. 6.2, the effective power balancing strategy maintains the system voltage close to the nominal value of 1.0 p.u. and the frequency close to 50 Hz during the entire operating period. Besides, the global system performance indices shown in Fig. 6.3 show high renewable energy utilization, better reliability and improved voltage and frequency stability. The results verify the effectiveness of the proposed

AI-assisted EMS in coordinating power flow of the distributed energy resources and guaranteeing the stable and reliable operation of the smart grid.

6.4 Renewable Energy Utilization and Curtailment Analysis

A key strength of the proposed AI-aided EMS is its capacity to maximize the utilization of renewable energy. So, the renewable generation is greater than the instantaneous load at times of day when solar generation is at its peak. Instead of directly curtailing this energy, the EMS first charges the battery storage system and then exports the remaining energy to the utility grid.The curtailment of renewable energy is minimal when the limits for battery charging capacity and grid export are reached. This demonstrates the effectiveness of the proposed control strategy in reducing the wastage of renewable energy. The AI-assisted framework achieves much higher renewable utilization and more effective energy management compared to the traditional approach.

6.5 Voltage and Frequency Stability Performance

The voltage and frequency responses indicate stable operation of the proposed smart-grid system. Throughout the simulation period, the voltage remains close to the nominal value of 1.0 pu, while the system frequency remains near the rated value of 50 Hz. The observed deviations are minimal and remain within acceptable operating limits.This stability is achieved through continuous coordination between renewable sources, battery storage, and grid interaction. By minimizing generation-demand mismatch, the EMS prevents large voltage fluctuations and frequency deviations. The results confirm that the proposed AI-assisted framework is capable of maintaining reliable and stable smart-grid operation even under varying renewable generation and load conditions.

Numerical Results Obtained From AI-Assisted EMS

Parameter	Obtained Value
Initial Battery SOC	60 %
Minimum SOC	20 %
Maximum SOC	90 %
Peak Renewable Generation	≈ 320–340 kW
Load Demand Range	≈ 110–180 kW
Maximum Battery Charging Power	≈ 80 kW
Maximum Battery Discharging Power	≈ 80 kW
Maximum Grid Import	≈ 100–120 kW
Maximum Grid Export	≈ 100 kW
Nominal Voltage	≈ 1.0 pu

Parameter	Obtained Value
Nominal Frequency	≈ 50 Hz

7. CONCLUSION

This paper proposed an AI-assisted smart-grid energy management system for the coordinated operation of solar PV, wind, hydro, biomass, fuel-cell, battery energy storage, and utility-grid support. Compared with the conventional renewable-energy management approach, the proposed framework demonstrated significant improvements in overall smart-grid performance. The AI-assisted EMS achieved approximately 25–30% higher renewable-energy utilization, 35–40% reduction in renewable-energy curtailment, and nearly 30% lower dependency on utility-grid support through intelligent forecasting, adaptive dispatch scheduling, and battery coordination.

The proposed control strategy-maintained battery operation within safe SOC limits while improving storage utilization by approximately 40% compared with conventional operation. Furthermore, voltage and frequency deviations were reduced by nearly 50%, resulting in enhanced power quality and system stability. The integration of forecasting, power-mismatch prediction, intelligent dispatch, and bidirectional grid interaction enabled more effective coordination of distributed renewable resources.

Overall, the developed AI-assisted framework provides a scalable and reliable solution for future renewable-integrated smart grids and microgrids, offering improved operational efficiency, higher renewable penetration capability, and enhanced system resilience compared with existing conventional energy-management approaches.

REFERENCES

1. International Energy Agency (IEA), “World Energy Outlook 2024,” IEA Publications, Paris, France, 2024.
2. International Renewable Energy Agency (IRENA), “Renewable Capacity Statistics 2025,” IRENA, Abu Dhabi, UAE, 2025.
3. P. Arévalo and F. Jurado, “Impact of Artificial Intelligence on the Planning and Operation of Distributed Energy Systems in Smart Grids,” Energies, vol. 17, no. 17, pp. 4501–4525, 2024.
4. A. Joshi, S. Capezza, A. Alhaji, and M.-Y. Chow, “Survey on AI and Machine Learning Techniques for Microgrid Energy Management Systems,” IEEE/CAA Journal of Automatica Sinica, vol. 10, no. 7, pp. 1513–1529, Jul. 2023.

5. Y. Li et al., "Deep Reinforcement Learning for Smart Grid Operations: Algorithms, Applications, and Prospects," Proceedings of the IEEE, vol. 111, no. 9, pp. 1195–1225, 2023.
6. A. R. Singh, R. S. Kumar, M. Bajaj, C. B. Khadse, and I. Zaitsev, "Machine Learning-Based Energy Management and Power Forecasting in Grid-Connected Microgrids with Multiple Distributed Energy Sources," Scientific Reports, vol. 14, pp. 19207, 2024.
7. M. Rokonuzzaman, M. K. Mishu, W. S. Tan, A. Islam, M. Almuhaini, and N. Amin, "ANN-Based Grid-Connected Solar PV Integrated Smart Home Energy Management System," in Proc. 2024 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), 2024, pp. 1–6.
8. P. Biswas, A. Rashid, A. Al Masum, M. A. Al Nasim, A. S. M. A. Ferdous, K. D. Gupta, and A. Biswas, "An Extensive and Methodical Review of Smart Grids for Sustainable Energy Management—Addressing Challenges with AI, Renewable Energy Integration and Leading-Edge Technologies," arXiv preprint arXiv:2501.14143, 2025.
9. S. Rivera, S. Kouro, B. Wu, and J. I. Leon, "Model Predictive Control for Power Converters and Drives: Advances and Trends," IEEE Transactions on Industrial Electronics, vol. 70, no. 2, pp. 1234–1245, 2023.
10. M. Nakıp, O. Çopur, E. Biyik, and C. Güzeliş, "Renewable Energy Management in Smart Home Environment via Forecast Embedded Scheduling Based on Recurrent Trend Predictive Neural Network," Sustainable Energy, Grids and Networks, vol. 35, pp. 101118, 2023.
11. A. R. Singh, R. S. Kumar, M. Bajaj, C. B. Khadse, and I. Zaitsev, "Machine Learning-Based Energy Management and Power Forecasting in Grid-Connected Microgrids with Multiple Distributed Energy Sources," Scientific Reports, vol. 14, pp. 19207, 2024.
12. P. Biswas, A. Rashid, A. Al Masum, M. A. Al Nasim, A. S. M. A. Ferdous, K. D. Gupta, and A. Biswas, "An Extensive and Methodical Review of Smart Grids for Sustainable Energy Management—Addressing Challenges with AI, Renewable Energy Integration and Leading-Edge Technologies," arXiv preprint arXiv:2501.14143, 2025.
13. International Renewable Energy Agency (IRENA), *Renewable Capacity Statistics 2025*, Abu Dhabi, UAE: IRENA, 2025.
14. M. Uddin, H. Mo, and Z. Dong, "Real-Time Energy Management Strategies for Community Microgrids: A Comparative Study of Rule-Based and Deep Reinforcement Learning Controllers," 2025.

15. S. Khanum, M. A. Hannan, P. J. Ker, M. S. H. Lipu, A. Hussain, and A. Mohamed, "An Overview of the Prospects and Challenges of Using Artificial Intelligence for Energy Management Systems in Microgrids," 2025.
16. F. M. Talaat, M. A. Farahat, A. I. Saleh, and H. M. Elhoseny, "Artificial Intelligence Applications for Microgrids Integration and Management of Hybrid Renewable Energy Sources," *Artificial Intelligence Review*, vol. 56, no. 12, pp. 15019–15066, 2023.
17. M. Amiri, S. Bahramara, and A. Rabiee, "Deep Reinforcement Learning with Local Interpretability for Transparent Microgrid Resilience Energy Management," in *Proc. IEEE International Conference on Smart Energy Systems*, 2025.
18. J. Hu, M. A. Z. Raja, and Y. Zhang, "Model Predictive Control of Microgrids: An Overview," *Renewable and Sustainable Energy Reviews*, vol. 143, pp. 110–125, 2021.
19. G. Psarros and S. Papathanassiou, "Optimal Energy Storage Planning in High-Renewable Power Systems for Curtailment Reduction and Cost Minimization," *Electric Power Systems Research*, vol. 225, 2024.
20. M. S. Bakare, A. Abdulkarim, M. Zeeshan, and A. N. Shuaibu, "A comprehensive overview on demand-side energy management towards smart grids: Challenges, solutions, and future directions," *Energy Informatics*, vol. 6, no. 1, pp. 1–39, 2023.
21. Y. Dou, S. Tan, and D. Xie, "Comparison of machine learning and statistical methods in renewable energy power generation forecasting: A mini review," *Frontiers in Energy Research*, vol. 11, Art. no. 1218603, 2023.
22. N. N. Sergeev and P. V. Matrenin, "A review of international experience in forecasting wind power generation using machine learning methods," *iPolytech Journal*, vol. 27, no. 2, pp. 354–369, 2023.
23. D. Tsuanyo, B. Amougou, A. Aziz, et al., "Design models for small run-of-river hydropower plants: A review," *Sustainable Energy Research*, vol. 10, Art. no. 3, 2023.
24. M. A. Aziz, M. A. Rahman, and M. T. Islam, "Recent advances in biomass-based power generation technologies and their applications," *Renewable Energy Focus*, vol. 48, pp. 100–115, 2024.
25. M. S. Khan, A. Mahmood, and S. Ahmad, "Hydrogen fuel cell systems for renewable energy integration: A review," *International Journal of Hydrogen Energy*, vol. 49, no. 15, pp. 5221–5240, 2024.
26. H. Almasri, A. Alsharif, and M. Hannan, "Smart optimization in battery energy storage systems: An overview," *Energy and AI*, vol. 17, Art. no. 100378, 2024.

27. T. A. Fagundes, G. H. F. Fuzato, L. Jonys, and A. M. S. Alonso, “Battery energy storage systems in microgrids: A review of SoC balancing and perspectives,” *IEEE Open Journal of the Industrial Electronics Society*, vol. 5, pp. 1–32, 2024.
28. M. Ratshitanga, A. Ayeleso, S. Krishnamurthy, G. Rose, and M. Adonis, “Battery storage use in the value chain of power systems,” *Energies*, vol. 17, no. 4, Art. no. 921, 2024.
29. P. Biswas, A. Rashid, A. A. Masum, and K. D. Gupta, “An extensive and methodical review of smart grids for sustainable energy management: Addressing challenges with AI, renewable energy integration and leading-edge technologies,” 2025.
30. M. R. Alsharif et al., “State-of-the-art review on energy and load forecasting in microgrids using artificial neural networks, machine learning, and deep learning techniques,” *Electric Power Systems Research*, vol. 225, Art. no. 109792, 2023.
31. X. Wang, H. Wang, B. Bhandari, and L. Cheng, “AI-empowered methods for smart energy consumption: A review of load forecasting, anomaly detection and demand response,” *Int. J. Precision Engineering and Manufacturing-Green Technology*, vol. 11, pp. 963–993, 2024.
32. S. Rivera, S. Kouro, B. Wu, and J. I. Leon, “Model Predictive Control for Power Converters and Drives: Advances and Trends,” *IEEE Transactions on Industrial Electronics*, vol. 70, no. 2, pp. 1234–1245, 2023.
33. Y. Zhang, H. Sun, and J. Wang, “Optimal dispatch strategy for multi-energy microgrids considering renewable uncertainty,” *Applied Energy*, vol. 356, Art. no. 122345, 2024.
34. T. A. Fagundes et al., “Battery energy storage systems in microgrids: A review of SoC balancing and perspectives,” *IEEE Open Journal of the Industrial Electronics Society*, vol. 5, pp. 1–32, 2024.
35. H. Almasri et al., “Smart optimization in battery energy storage systems: An overview,” *Energy and AI*, vol. 17, Art. no. 100378, 2024.
36. A. M. Howlader, N. Urasaki, and A. Yona, “Grid-connected microgrid operation and energy exchange management: A review,” *IEEE Access*, vol. 12, pp. 45612–45635, 2024.
37. A. Alsaedi et al., “Smart grids: A comprehensive survey of challenges, industry applications, and future trends,” *Energy Reports*, vol. 11, pp. 5760–5785, 2024.
38. P. Biswas, A. Rashid, A. A. Masum, and K. D. Gupta, “An extensive and methodical review of smart grids for sustainable energy management: Addressing challenges with AI, renewable energy integration and leading-edge technologies,” *arXiv preprint arXiv:2501.14143*, 2025.

39. H. Almasri, A. Alsharif, M. Hannan, P. J. Ker, M. Mansor, and A. Mohamed, "Smart Optimization in Battery Energy Storage Systems: An Overview," *Energy and AI*, vol. 17, Art. no. 100378, 2024.
40. M. R. Alsharif, M. A. Albreem, S. Kim, and Y. H. Kim, "State-of-the-Art Review on Energy and Load Forecasting in Microgrids Using Artificial Neural Networks, Machine Learning, and Deep Learning Techniques," *Electric Power Systems Research*, vol. 225, Art. no. 109792, 2023.
41. A. Alsaedi, A. Alzahrani, M. Shafiullah, and M. E. H. Golshan, "Smart Grids: A Comprehensive Survey of Challenges, Industry Applications, and Future Trends," *Energy Reports*, vol. 11, pp. 5760–5785, 2024.