ARTIFICIAL INTELLIGENCE BASED ENERGY MANAGEMENT FOR GRID-CONNECTED PV–BATTERY SYSTEMS: A REVIEW

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ABSTRACT

The increasing integration of photovoltaic (PV) generation and battery energy storage systems (BESS) into grid-connected power systems presents energy management challenges arising from renewable generation variability, load-demand uncertainty, battery degradation, electricity-price fluctuations, and changing grid conditions. Conventional energy management systems (EMS) often have limited capabilities for adapting to these uncertainties while coordinating economic operation, battery constraints, and grid stability. This review critically examines developments in intelligent EMS for grid-connected PV–battery systems, focusing on forecasting, energy scheduling, optimization, battery management, and grid-support control. A systematic literature review was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to identify, screen, assess, and synthesize relevant studies published between 2020 and 2026. A total of 75 studies were included in the final review. The synthesis identifies persistent challenges in uncertainty quantification, real-time adaptability, battery degradation awareness, computational complexity, reinforcement-learning safety, and the integration of energy management with grid-forming inverter control. To address these gaps, a hierarchical energy management framework is proposed, combining Bayesian Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) forecasting for uncertainty-aware prediction, Soft Actor-Critic (SAC) reinforcement learning for adaptive energy scheduling, Stochastic Model Predictive Control (SMPC) for constraint-aware optimization, and Virtual Synchronous Machine (VSM)-based grid-forming inverter control for voltage and frequency support. The proposed framework provides a basis for future simulation-based investigation of integrated, adaptive, and uncertainty-aware energy management in grid-connected PV–battery systems.

Keywords: *Energy Management System; Battery Energy Storage System; Artificial Intelligence; Stochastic Model Predictive Control; Grid-Forming Inverter.*

1 INTRODUCTION

The integration of photovoltaic (PV) generation and battery energy storage systems (BESS) into grid-connected power systems offers opportunities to increase renewable energy utilization, improve energy flexibility, and reduce dependence on conventional electricity generation [1]. However, the variable nature of solar irradiance, fluctuations in electricity demand, battery operating limitations, and changing grid conditions complicate the coordination of generation, storage, and power exchange [2]. An effective Energy Management System (EMS) is therefore required to balance power supply and demand, coordinate battery charging and discharging, minimize operating costs, preserve

battery health, and support reliable grid operation [3]. These objectives become more challenging when PV generation and load demand are uncertain and operational decisions must satisfy technical and economic constraints simultaneously [4]. Existing Energy Management System (EMS) approaches range from rule-based strategies to optimization-based and artificial intelligence (AI)-driven methods. Rule-based EMS relies on predefined operating conditions and is relatively simple to implement, but its adaptability may be limited when operating conditions differ from those anticipated during design [5]. Conventional optimization techniques, including linear and model predictive optimization, can systematically coordinate energy resources subject to defined constraints; however, their performance depends on model accuracy, computational requirements, and the treatment of uncertainty [6]. Forecasting-based EMS incorporates PV generation and load predictions to support scheduling decisions, while machine-learning and deep-learning methods offer additional capabilities for modelling complex relationships in historical and operational data. Reinforcement learning has also been investigated for adaptive energy scheduling through interaction with an operating environment. Furthermore, hybrid AI–optimization frameworks combine predictive models or learned policies with optimization methods to improve decision-making under operational constraints [7]. Despite these developments, several issues require further investigation. First, accurate forecasting does not necessarily guarantee reliable energy scheduling when prediction uncertainty is not explicitly quantified [8]. Second, learned Energy Management System (EMS) policies may experience reduced performance under operating conditions that differ from their training environments [9]. Third, battery degradation and state-of-health considerations may receive insufficient attention when scheduling objectives prioritize short-term cost or power balance. In addition, computational burden can restrict the practical application of complex methods, while constraint enforcement remains important for maintaining safe battery operation and feasible power exchange [10]. Finally, energy scheduling performance and grid stability are not always evaluated together, limiting understanding of how EMS decisions interact with voltage and frequency support [11]. These gaps should be interpreted in accordance with the evidence established by the studies reviewed in this paper. This review systematically examines developments in intelligent Energy Management System (EMS) for grid-connected PV–battery systems using the PRISMA 2020 framework. Unlike an assessment limited to individual forecasting or scheduling algorithms, it organizes and compares existing approaches across four connected functions: PV and load forecasting, adaptive energy scheduling, operational constraint handling, and grid-support control. It also examines reported evaluation metrics, implementation approaches, and limitations to identify research gaps and future research priorities. Based on the synthesis, a prospective hierarchical framework combining Bayesian CNN–LSTM forecasting, Soft Actor-Critic (SAC) reinforcement learning, Stochastic Model Predictive Control (SMPC), and Virtual Synchronous Machine (VSM)-based grid-forming inverter control is outlined for future investigation. The remainder of this paper presents the literature reviews, review methodology, and synthesized findings. Subsequent sections discuss related works, research gaps and future directions before concluding with the principal implications of the review.

2 LITERATURE REVIEW

2.1 Overview of Energy Management Systems

EMS play a vital role in coordinating energy generation, storage, loads, and grid interaction to ensure reliable, efficient, and economical operation of renewable-integrated power systems [12]. The primary objectives of EMS include maximizing renewable energy utilization, minimizing operating costs, preserving battery health, maintaining power balance, regulating voltage and frequency, and enhancing overall grid stability [13]. Modern EMS operates through a continuous cycle of data acquisition, renewable and load forecasting, decision-making, optimization, and real-time control [12]. Advanced artificial intelligence techniques, including machine learning, deep learning, reinforcement learning, Bayesian learning, and MPC, have significantly improved forecasting accuracy, adaptive decision-making, uncertainty management, and system resilience like support grid stability [14]. These intelligent techniques

are driving the development of resilient, autonomous, and highly efficient smart energy management systems for future renewable power networks [15, 14].

2.2 Rule-Based Energy Management Systems (EMS)

Rule-Based EMS are commonly utilized in grid-connected photovoltaic and battery storage systems due to their simplicity and low computational need [16]. They function based on predefined IF–THEN rules that consider variables like PV output and battery state of charge (SOC) to manage energy flow. Typical actions include charging batteries with excess generation, importing grid power when SOC is low, and discharging during peak prices. Despite their cost-effectiveness, they lack adaptability to changing conditions and renewable energy uncertainties, limiting scalability and learning capabilities, which necessitates the transition to AI-based EMS for better predictive and adaptive energy management [14].

2.3 Classical Optimization-Based Energy Management Systems

Classical optimization-based EMS focus on optimizing energy scheduling in grid-connected photovoltaic and battery systems to minimize costs, maximize renewable energy use, prolong battery life, and maintain power balance [17]. Techniques such as Linear Programming, Mixed Integer Linear Programming, Dynamic Programming, Genetic Algorithms, and Particle Swarm Optimization are commonly employed to optimize battery and grid power exchanges. However, these methods are limited by their reliance on deterministic models and historical data, which renders them less effective in the face of renewable energy uncertainties and dynamic conditions, alongside high computational complexity. This has prompted a shift toward AI-based EMS, which offers predictive, adaptive, and uncertainty-aware management solutions for modern smart grids [18, 15].

2.4 Machine Learning-Based Energy Management Systems (ML - EMS)

ML - EMS improve grid-connected photovoltaic (PV) and battery storage operations by leveraging historical and real-time data for better forecasting, optimization, and control [19]. Unlike traditional rule-based systems, ML algorithms like ANN and Support Vector Machines (SVM) can uncover complex nonlinear relationships, enhancing prediction accuracy for solar generation and electricity prices [20]. However, these systems require large, high-quality datasets and often generate deterministic predictions that fail to account for uncertainty [12]. Additionally, they struggle with real-time adaptive decision-making in rapidly changing conditions, prompting the exploration of advanced AI methods such as Bayesian learning and reinforcement learning for improved adaptability in energy management.

2.5 Deep Learning and Bayesian Learning for Renewable Energy Forecasting

Accurate forecasting is essential for Energy Management Systems (EMS) in grid-connected photovoltaic and battery storage systems, as it supports optimal energy scheduling and grid interactions [21]. Deep learning techniques, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer networks, enhance forecasting accuracy by learning nonlinear relationships from large datasets but often lack uncertainty quantification. Bayesian Deep Learning (BDL) improves this by combining deep learning with probabilistic inference, providing confidence intervals for more reliable energy management [21]. A proposed hybrid Bayesian CNN-LSTM framework aims to combine the spatial feature extraction of CNNs with the temporal learning of LSTMs, further enhancing accuracy and uncertainty awareness for EMS in renewable-rich smart grids.

2.6 Reinforcement Learning for Intelligent Energy Management Systems

Reinforcement Learning (RL) is an AI technique allowing EMS to establish optimal control strategies through trial and error. In grid-connected photovoltaic and battery systems, the state includes factors like battery state of charge, PV generation, and load demand, while actions involve battery

management and load scheduling [22]. The aim is to optimize long-term rewards by reducing costs and enhancing grid stability. Deep Reinforcement Learning (DRL) incorporates deep neural networks for complex environments, with algorithms like Deep Q-Network (DQN) and Soft Actor-Critic (SAC) being particularly effective [23]. SAC is favored for its stability and efficiency in adaptive energy management [23]. However, challenges remain, including slow convergence and high computational needs, prompting research into integrating RL with optimization methods like Model Predictive Control (MPC) for improved performance in smart grids.

2.7 Model Predictive Control and Stochastic Model Predictive Control

Optimization is critical in modern Energy Management Systems (EMS) for managing distributed energy resources and enhancing renewable energy usage while reducing costs. Key objectives include efficient energy scheduling and maintaining reliability despite fluctuations in renewable inputs [13]. Model Predictive Control (MPC) is widely used in EMS for optimizing battery and grid interactions. It outperforms traditional methods like Linear Programming and Genetic Algorithms due to its real-time adaptability. Stochastic Model Predictive Control (SMPC) further enhances MPC by factoring uncertainties in solar irradiance, demand, and pricing, using probabilistic forecasting to minimize costs while meeting system constraints. Though SMPC improves reliability and efficiency, it requires accurate models and lacks autonomous learning, prompting research into combining it with AI techniques for developing adaptive energy management systems for future smart grids [14].

2.8 Grid-Forming Inverters for Grid Stability in Renewable Energy Systems

The rapid integration of renewable energy sources, including photovoltaic (PV) systems, wind turbines, and battery energy storage systems (BESS), has transformed modern power systems but introduced significant stability challenges [15]. Unlike conventional synchronous generators, inverter-based renewable energy sources provide little or no inherent inertia, resulting in increased frequency deviations, voltage instability, weak-grid conditions, and reduced fault tolerance [24]. Conventional grid-following inverters depend on an existing grid voltage and frequency reference, limiting their performance during grid disturbances, islanded operation, or weak-grid scenarios [25]. To overcome these limitations, Grid-Forming Inverters (GFMs) have emerged as a key technology for future renewable-dominated power systems. Unlike grid-following inverters, GFMs operate as controlled voltage sources capable of independently establishing and regulating grid voltage and frequency without external synchronization. This enables them to provide virtual inertia, voltage regulation, frequency support, black-start capability, and reliable power sharing among distributed energy resources. Consequently, GFMs significantly enhance grid resilience, improve power quality, and ensure stable operation under both grid-connected and islanded conditions. Their ability to emulate the behavior of synchronous generators makes them an essential component of intelligent, renewable-integrated smart grids and future autonomous energy systems [12].

2.9 Virtual Synchronous Machine (VSM) for Grid-Forming Inverters

The Virtual Synchronous Machine (VSM) is a widely adopted control strategy that enables Grid-Forming Inverters (GFMs) to emulate the dynamic behavior of conventional synchronous generators [26]. By implementing the synchronous machine swing equation through software, VSM provides synthetic inertia and damping, allowing the inverter to regulate voltage and frequency while responding effectively to power imbalances [27]. This capability enhances frequency stability, suppresses oscillations, and improves system resilience, particularly in weak-grid and renewable-dominated power systems. VSM-based GFMs also support voltage regulation, fault ride-through capability, black-start operation, and reliable power sharing among distributed energy resources [26]. Despite these advantages, VSM implementation requires accurate parameter tuning, sophisticated control design, and significant computational resources to ensure stable real-time operation. Recent advances in artificial intelligence, reinforcement learning, and high-performance embedded controllers are improving VSM performance, making it a key technology for future resilient and sustainable smart grids.

3 METHODOLOGY

This review used the PRISMA 2020 framework to systematically examine the literature on AI-driven Energy Management Systems (EMS) for grid-connected photovoltaic-battery systems [28]. PRISMA was chosen for its structured approach and reduction of selection bias. It explored recent advancements in energy management techniques, including various optimization and learning algorithms, as well as battery management strategies and grid-support technologies. The review followed four stages: Identification, Screening, Eligibility Assessment, and Final Inclusion, adhering to PRISMA 2020 guidelines for transparency and consistency. A comprehensive literature search was conducted to identify peer-reviewed studies on artificial intelligence (AI)-driven energy management in renewable energy systems. Relevant publications were retrieved from IEEE Xplore, ScienceDirect (Elsevier), SpringerLink, Wiley Online Library, MDPI, Taylor and Francis, Nature Portfolio, Google Scholar, and Scopus. The review considered articles published between **2020 and 2026** to capture recent advances in AI, battery energy storage management, renewable energy integration, and smart grid technologies. A systematic search strategy was employed using Boolean operators (**AND** and **OR**) to combine keywords, including Energy Management System (EMS), Artificial Intelligence, Machine Learning, Deep Learning, Bayesian Deep Learning, CNN – LSTM, Reinforcement Learning, Soft Actor-Critic, Model Predictive Control, Stochastic MPC, Battery Energy Storage System, Battery Management System, Grid-Connected PV Systems, Photovoltaic, Renewable Energy, Smart Grid, Grid-Forming Inverters, Virtual Synchronous Machines, Microgrid Energy Management, and Renewable Energy Forecasting. This strategy ensured the identification of high-quality studies relevant to intelligent energy management, uncertainty-aware control, battery optimization, and grid-support applications. To ensure the quality and reliability of the literature review, specific inclusion and exclusion criteria were established. Studies published between 2020 and 2026 as peer-reviewed articles in English were included, focusing on artificial intelligence-based energy management systems (EMS) for renewable energy, especially grid-connected photovoltaic-battery systems. Selected papers explored intelligent energy management aspects like renewable energy forecasting, optimization, and control strategies, providing validated quantitative performance indicators. Exclusions involved review articles lacking original contributions, unrelated studies, articles without full text, duplicates, and those concentrating solely on hardware design without energy management strategies or artificial intelligence techniques. The study selection and data extraction process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a transparent and systematic review. Relevant studies were identified from major scientific databases, screened for duplicates, and evaluated through title, abstract, and full-text assessments based on predefined inclusion and exclusion criteria. Eligible studies were categorized according to forecasting, battery management, optimization, reinforcement learning, deep learning, Bayesian learning, grid-support control, and hybrid AI architectures. Key information extracted included authors, publication year, research objectives, AI techniques, energy management approaches, performance metrics, major findings, limitations, and identified research gaps.

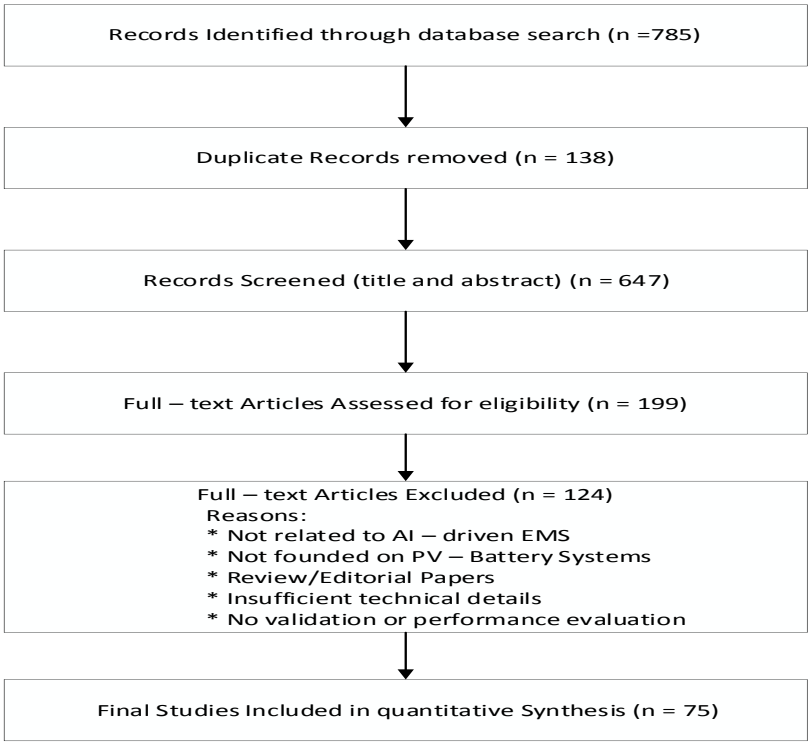


Figure 1. PRISMA 2020 Literature Selection [28]

Table 1. PRISMA-based literature identification and screening process

PRISMA Stage	Number of Records
Records identified through database searching	785
Duplicate records removed	138
Records screened (title and abstract)	647
Records excluded after screening	448
Full-text articles assessed for eligibility	199
Full-text articles excluded	124
Studies included in the qualitative review	75

4 RELATED WORKS AND RESEARCH GAP

This paper [29] proposed a hybrid Model Predictive Control (MPC) and Dynamic Programming (DP) framework for residential PV–battery energy management. Using a 24-hour receding horizon, the framework minimized operating costs, enhanced grid stability, and increased self-consumption. However, its performance depended heavily on forecasting accuracy and involved high computational complexity. Future research should integrate AI-based forecasting and intelligent optimization techniques to improve adaptability and operational efficiency. This work [30] proposed an integrated control strategy for MPPT, battery SOC balancing, and DC bus voltage regulation in PV–battery systems. The framework achieved 94.2% energy conversion efficiency and improved SOC stability. However, it increased computational complexity and was limited to lithium-ion batteries. Future work should investigate AI-based MPPT and predictive energy management techniques. This study [31] develops a CNN-BiLSTM-based EMS for a grid-connected PV-battery EV charging station, validated using Hardware-in-the-Loop. Trained on 50,000 synthetic samples, the model achieved an RMSE of 0.045, R^2 of 0.97, and 88–93% efficiency. However, reliance on synthetic data, absence of real-world deployment and economic analysis, and limited degradation consideration highlight the need for stochastic optimization and practical implementation. This

research [32] proposes a three-phase AI-based EMS integrating PLSTM load forecasting, ANN-based PV forecasting, and a robust hierarchical EMS using two-layer MPC. The approach achieved 28% reduction in grid import and 15% improvement in SOC tracking. However, computational burden, limited IoT integration, and dynamic modeling constraints remain. Future research should explore Edge-AI distributed MPC, federated learning, and cyber-resilient EMS architectures. This study [33] investigates a 5 kW PV-based DC microgrid incorporating a hybrid energy storage system comprising lithium-ion batteries and a supercapacitor. RBFNN-based MPPT achieved 97.25% efficiency, while NARX supported energy management. The system improved DC-bus voltage stability, SOC regulation, battery stress reduction, and robustness. However, simulation-based validation, fixed system capacity, and lack of economic optimization and real-time implementation remain limitations. This work [34] develops a cost-effective EMS for grid-connected PV microgrids using lithium-ion battery storage and variable loads. Three approaches—heuristic, linear programming, and fuzzy logic—were compared in MATLAB/Simulink. The proposed FLC-EMS achieved 8.1–16.6% and 1.6–5.5% cost reductions, respectively, while improving battery SOC management and grid utilization. However, real-time validation and scalability remain limitations requiring further investigation. This paper [35] presents a three-layer predictive EMS comprising logical control, forecasting, and optimization. Res-DCCN models achieved 93.08% PV and 97.25% load forecasting accuracy, while multi-objective optimization reduced grid purchases, improved battery SOC, and lowered CO_2 emissions. However, the study is limited to PV–battery–grid systems, single-step forecasting, simulations, and no hardware validation. Future research should consider digital twins, battery health, and multi-source integration. This study [36] proposes a multi-layer control architecture for solar PV–battery EV charging stations using a Landsman converter and RBFNN-based MPPT. The system achieved 98.12% converter efficiency, effective MPPT performance, and IEEE 519-compliant power quality. However, limitations include computational complexity, absence of hardware validation, and limited real-world analysis. Future research should investigate Deep Reinforcement Learning, digital twins, fault analysis, and hardware implementation. This research [37] proposes a hybrid HESS optimization-control framework integrating MPC, PSO, MILP, and ANN for real-time control, storage sizing, scheduling, and SOC/grid-stability prediction. The approach reduced system cost from $1.8M to $1.6M, lowered energy losses by 15.8%, and achieved 95.1% prediction accuracy. However, computational complexity and lack of field validation remain limitations. Future work should investigate DRL, cybersecurity, and multi-storage optimization. This work [38] presents an Enhanced EMS for microgrids integrating PV, battery storage, and AC grids using EFIAGNN and MBGIO. The framework achieved 95% energy management efficiency, reduced operational costs to $1,700, and maintained low voltage deviation of 0.68%. However, algorithmic complexity, data dependency, scalability, and lack of hardware validation remain limitations. Future research should emphasize real-time testing, Digital Twins, robustness, and advanced machine learning integration. This study [39] investigates Hybrid Renewable Energy Systems integrating PV, wind, BESS, and diesel generation using TD3-based Deep Reinforcement Learning. The approach optimizes cost, reliability, and renewable penetration, achieving significant cost reductions and adaptability. However, high training complexity, limited energy-source modeling, and lack of real-world validation remain limitations. Future research should integrate renewable forecasting, real-time adaptive control, and hybrid DRL-MPC strategies for improved performance. This research [40] presents a dual-layer optimization framework combining Genetic Algorithm (GA) for optimal system sizing with Model Predictive Control (MPC) for real-time energy management. GA minimizes NPC, COE, and LPSP, while MPC reduces grid import costs and manages battery operation. A UCSD case study demonstrated cost savings and reduced grid dependence. However, electrical dynamics, stability, and cybersecurity were not considered. Future work should incorporate AI, dynamic modeling, and fault management.

Table 2. Related works and research gaps on AI-based energy management for grid-connected PV–battery systems literatures

Ref	Methodology	Key Finding	Research Gap
[41] 2024	SVR for energy management and renewable power forecasting in microgrids (PV, wind, fuel cells, battery, utility grid)	MSE: 2.002 (solar), 3.059 (wind); reduced operating costs; better supply-demand balance	Need for hybrid ML models (LSTM-Transformer), real-time frameworks, probabilistic forecasting, and multi-objective optimization
[42] 2025	HOMER Pro techno-economic optimization for hybrid microgrid (PV, VAWT, BESS) + Random Forest Regressor prediction	COE: \$0.035/kWh; NPC: \$18,265; RF: 68.3%; payback: 5.67 years; 49.6% CO_2 redu ction	Need for enhanced forecasting methods, adaptive control systems, broader geographical studies, hybrid ML approaches, and improved battery models
[43] 2024	ML framework: RF, SVR, LR for energy prediction; LSTM for load forecasting; ANN for SoC; Python Tkinter GUI	RF outperforms SVR/LR for solar/wind; LSTM excels in load forecasting; ANN high accuracy in SoC	Integration with EVs, IoT monitoring, cost optimization, advanced ML models; need probabilistic LSTM forecasting, MPC optimization, enhanced interpretability
[44] 2026	Dual-module: MLP ANN forecasting + Linear Programming optimization for grid-connected PV-BESS in multi-apartment buildings	Significant cost reductions; high self-consumption rates; robust optimization sensitive to forecast errors	Need for multi-market participation, real-time optimization adaptations, hierarchical optimization, and enhanced forecasting techniques
[45] 2025	Seven-step data-driven framework: RF and DNN for PV forecasting (mono-Si, poly-Si, a-Si) using 2-year Moroccan data	$R^2 > 0.98$ for both RF and DNN; RF outperforms DNN; a-Si most effective due to lower temperature coefficient	Geographic diversification, incorporation of additional features, hybrid modeling techniques for variable weather conditions
[46] 2020	Theoretical analysis + mathematical proofs + small-signal model for advanced droop control in Networked Microgrids	Improved power sharing; stability insights; enhanced power quality; universal Optimal Voltage Regulator (OVR) framework	Need for robust adaptive control, real-time considerations, unified adaptive OVR framework with real-time impedance estimation and decentralized control strategies
[47] 2024	ANN-based Adaptive PI Controller with droop control + Virtual Impedance Technique; MATLAB/Simulink simulations	Rise time reduction: 60%; overshoot: up to 80%; THD reduction in voltage and current	Need for HIL testing, robustness against faults and cyber-attacks, online ANN retraining, Type-2 fuzzy logic, enhanced testing conditions
[48] 2026	Multi-stage: stochastic modeling + metaheuristic optimization; single-diode PV model; SOC dynamics; Latin Hypercube Sampling	Load-side uncertainties affect outcomes more than irradiance; practical capacity guidelines	Need for extreme weather event consideration, cybersecurity threats, multi-building cluster approaches, advanced climate modeling

Ref	Methodology	Key Finding	Research Gap
[49] 2025	ANN-based MPPT (3-layer feedforward, Levenberg-Marquardt) + fuzzy logic EMS for grid-connected PV	5% MPPT efficiency improvement; faster convergence (0.14s vs 0.15s); reduced oscillations (3.8W vs 22W); SOC 20-80% range	Need for HIL validation, real-time testing, weather/load forecasting, advanced battery models (EKF), global MPPT testing under partial shading, techno-economic analysis
[50] 2025	Bayesian Deep Learning: VAE-Bayesian BiLSTM + Alpha-Beta Divergence BiLSTM + GMM-based load forecasting	97.35% dimensionality reduction; RMSE improvement: 14.12%; MAE: 22.6%	Need for improved uncertainty modeling, explainability, validation, generalization, real-time deployment; propose Hybrid Bayesian Reinforcement Learning Framework
[51] 2024	Six-stage: Weibull distribution + Z-score + FFT + Adam-optimized Bayesian RNN (8 wind farms, Dynamic Pressure Tube sensors)	MAE: 0.0152; R^2: 0.9862; probabilistic forecasting; non-linear handling	Need for LSTM alternatives, transformer integration, scalable frameworks, physics-informed comparisons, uncertainty quantification; propose Physics-Informed Bayesian RNN with Attention
[52] 2025	GCM-EM model: PV, BES, CHP, DRR; SoE optimization; 4 variants; real-world validation across 3 testbeds; MQTT communication	2% energy cost reduction; 3% annual energy + degradation cost reduction; battery lifespan: ~15.5 years	Need for stochastic programming, blockchain-based coordination, temperature-aware aging modeling, EV integration; propose Uncertainty-Aware, Multi-Chemistry Battery Degradation with stochastic MPC + blockchain
[53] 2026	Adaptive multi-objective DQN with Double Q-learning + Dueling networks for grid-connected microgrid (300 kWp PV, 500 kWh/150 kW battery)	12.01% operational cost reduction; 8.19% battery fade reduction; 13.75% CO_2 reduction; <25% forecast error	Need for multi-agent reinforcement learning, real-world deployment, coordinated microgrid management; constraint violation mitigation
[54] 2024	DRL-QIGA: Deep RL (real-time) + Quantum-inspired GA (global search); Weibull/Beta distributions; modified IEEE 30-bus	Fuel cost: $620.45; Power loss: 5.0 MW; outperforms existing algorithms in convergence speed	Need for hybrid deep learning, scalability, real-time applications; propose Multi-Objective Meta-Learning with Adaptive DRL-QIGA for further fuel cost and speed improvements
[55] 2024	MDP + DDPG algorithm for online BESS scheduling (two-part tariff); continuous action spaces	3.29% cost reduction vs PV-only; DDPG significantly outperforms DQN	Need for uncertainty modeling, offline optimal benchmarks, multi-day peak shaving, real-time hardware deployment; propose 6-8% savings via improved forecasting + transfer learning
[56] 2025	GrCRA + PCRTAM-Net hybrid optimization-prediction framework; 5kW PV, 3.5kWh battery, supercapacitor	Operational cost: 1505 cents; 99.1% efficiency; 60.3 ppm emissions	No real-world validation; idealized conditions; neglects battery aging; need hardware validation, battery aging models, cybersecurity, lightweight EMS with real-time forecasting and DR

Ref	Methodology	Key Finding	Research Gap
[57] 2023	GBDT-BiLSTM with Teacher Forcing; 18-month PV data from Sichuan, 30% missing data	MAE: 0.102; MSE: 0.128; outperforms SVM and Transformer; robust to missing data	Relies on GBDT quality; geographic specificity; high computational cost; need alternative boosting methods, diverse geographical testing, probabilistic forecasting, adaptive sampling
[58] 2025	SAC deep RL for HEV energy management; multi-cycle training; charge-sustaining modes	CO_2: 136.2 g/km (WLTC); convergence ~140 episodes; outperforms DDQL	No charge-depleting strategies; no connectivity data; reward tuning challenges; computational costs; need vehicle connectivity data and transfer learning
[59] 2024	SAC DRL for home EMS with PV, WT, battery, TOU pricing; comprehensive load model (interruptible/uninterruptible)	Daily cost: 18.34→15.43 RMB (15.87% reduction); outperforms Stochastic Programming	EVs treated only as loads; no V2G; no stochastic renewable modeling; need V2G, real-time pricing adaptations, multi-home coordination; propose Multi-Objective SAC with V2G and Uncertainty-Aware Forecasting
[60] 2026	Bayesian Transformer with PatchTST; MC Dropout + Variational FF + Stochastic Attention; 168-hour lookback	MAE: 1,573 MW; outperforms LSTM and Deep Ensembles; first Bayesian attention use	Inexact Bayesian inference; static calibration; high computational cost; no spatial correlation; need spatio-temporal Bayesian transformers with NWP ensemble predictions
[61] 2024	SMPC with Wasserstein ambiguity sets; data-driven model augmentation; decentralized droop + centralized MPC; IEEE 9-bus	9.23% reduction in constraint violations; frequency RMSE: 0.029477→0.022536 rad/s	Gaussian disturbance assumptions; tested only on IEEE 9-bus; need refined disturbance estimation, decentralized SMPC, DD-SMPC-Bayes
[62] 2024	Hierarchical-SMPC: upper SMPC (Gaussian) + lower PMPC; two-layer structure with chance constraints	1.0% cost reduction; 81% decrease in comfort violations vs HMPC	Relies on Gaussian assumptions; single winter validation; no EV integration; need scenario-based SMPC with deep learning
[63] 2026	"Cleaning-to-Stability" AI: 4-stage data cleaning + LSTM; 3-year hourly Iranian wind data	R^2=0.988 (Zabol); 30% OPEX reduction; 93-98% variance reduction	Relies on simulated data; potential climate shift oversights; need CNN-LSTM architectures, digital twin technologies; propose PINN-XAI Hybrid with Digital Twin
[64] 2026	MOSSA + MOWOA; rule-based EMS; PV, WT, BES, DG; 3 load scenarios (5,10,15 houses)	LPSP: 0.098%; Renewable Fraction: 94.08%; best COE: $0.165/kWh (PV/WT/BES, 10 houses)	Deterministic load modeling; no predictive EMS; need stochastic modeling, AI-driven solutions; propose Uncertainty-Aware Hybrid EMS with DRL and Multi-Year Optimization
[65] 2026	Two-stage LSTM autoencoder: nonlinear regression + residual learning; SHAP feature selection	MAE: 2.7080→1.3864 kW (48.8% reduction); R^2: 0.9467→0.9882; cross-site MAE: 1.2016 kW	Persistence outperforms ML models; high training time; no uncertainty quantification; need Transformer architectures, probabilistic forecasting, real-time adaptive learning

Ref	Methodology	Key Finding	Research Gap
[66] 2021	Two-layer: MILP (day-ahead) + SMPC (real-time); disturbance-feedback policies; MG²Lab validation	1.7% cost discrepancy; 2.7% fuel consumption reduction vs traditional	SOC estimation errors; constant battery efficiency assumptions; need stochastic formulations for first layer, enhanced inter-layer interaction, complex microgrids
[67] 2024	TCN + ECANet + GRU; dilated causal convolutions; 5 residual blocks; DKASC Australia data	RMSE: 0.0195; R^2: 99.72%; significant multistep improvements	5-min predictions only; max horizon 45 min; no probabilistic forecasting; no feature selection; need longer horizons, deeper feature correlation; propose Probabilistic TCN-ECANet-GRU with Physical Prior and EMS Integration
[68] 2025	Three-stage: MIC feature selection + Bayesian CNN-BiLSTM-Attention + K-shape clustering + ABKDE; 50 MW Xinjiang PV plant	MAE: 0.820 MW; RMSE: 1.416 MW; 98.21% coverage at 95% confidence (sunny)	Short dataset; no seasonal variability; no cross-climate validation; need extended forecast horizons, diversified datasets, physical models, real-time applicability; propose Multi-Site, Multi-Horizon Probabilistic Forecasting with Interpretable Uncertainty Decomposition
[69] 2025	DL-PEM + MOPSO; 5 modules (IoT, preprocessing, SHAP, DNN, MOPSO); HVAC and lighting optimization	99.8% occupancy prediction; 85% optimization efficiency; CO_2 and light key features	Relies on sensor accuracy; computational demands; no real-world deployment; need edge deployment, renewable integration, scalability; propose Edge-Deployable, Transferable, Multi-Zone DL-PEM-MOPSO
[70] 2025	AMPC: offline RL (COA-jDE) + online MPC with soft constraints; 16 MW microgrid, 8×2 MW DFIG	23.6% reduction in frequency deviation; faster synchronization vs VSM; meets grid codes	Offline reliance on grid modeling accuracy; no hardware validation; need distributed control, real-time implementations; propose Distributed, Hardware-Validated, Multi-Renewable AMPC
[71] 2025	AP-VSG control for SEIGs; adaptive inertia and damping; multi-objective predictive optimization	RoCoF: 0.48→0.21 Hz/s; 20% settling time improvement; 33% frequency nadir; 36.7% control effort reduction	SEIG-specific reactive power; vulnerability to blackouts; unspecified communication delays; need ML for real-time adjustments, hybrid energy systems; propose ML-Enhanced, Multi-AP-VSG Consensus Control
[72] 2023	SMPC with MLD framework; three-state automata; Big-M formulations; hydrogen + battery storage; 4 modes	State switches reduced 80-95%; computation time reduced 80%	Fixed probability for scenarios; no regulation/ancillary services; convergence issues in open-source solvers; need regulation services, price uncertainty modeling, real-time hardware validation; propose Multi-Scenario SMPC with Adaptive Weighting
[73] 2021	SMPC with GBRT probabilistic forecasting (19 quantiles) + Gaussian copula scenario generation; residential PV-battery	Self-consumption: 0.47→0.49 p.u.; Self-sufficiency: 0.58→0.60 p.u.; Profit: 3.55→3.81 SEK	Short testing window; limited data; deterministic pricing; need extended testing, varying battery parameters, battery degradation costs; propose Multi-Time-Scale SMPC with Adaptive Scenario Selection

Ref	Methodology	Key Finding	Research Gap
[74] 2026	IPOEMS: Arduino hardware + S-TCNN (Swish) + EOA + AES encryption; PV single-diode + SOC battery model	94% SOC prediction accuracy; 1.2% energy conversion loss; outperforms DDQN, LSTM, GAN	No real-world validation; dataset transparency issues; no comprehensive load modeling; need laboratory validation, real-time pricing, Edge-Federated IPOEMS (EF-IPOEMS)
[75] 2024	GEP-optimized ANFIS (Takagi-Sugeno); double-diode PV; TOU pricing; Global Tea Company Uganda data	MAPE: 2.24% (load forecasting); LCOE: $0.061/kWh (Grid/Solar PV/Battery)	No real-time implementation; limited reproducibility; no deep learning comparisons; high computational complexity; need efficient training, advanced hybrid models; propose Digital Twin-Enabled GEP-ANFIS with RL (DT-GEP-ANFIS-RL)
[76] 2025	5-layer AI: RL-ENN-MOO + T-STFREP (Transformer) + FL-DEO + GNN-HSCO + Q-GAN-ESO; grid-tied PV-fuel cell	27.5% NPC reduction; 18.2% COE reduction; solar MAPE 2.1%; wind MAPE 3.2%	High computational demands; data accuracy issues; need enhanced federated learning, Hybrid Digital Twin Integration
[77] 2025	Monte Carlo-driven NSGA-II; two-diode PV models; 12 decision variables; KNUST campus Ghana	PV penetration: 86.12%; Total losses: 13.89%	Computational complexity; geographic constraints; no economic indicators; need diverse climatic validations, power quality assessments
[78] 2026	NP model with Optuna hyperparameter optimization; trend, seasonal, holiday, autoregressive terms; 3-year SCADA data	RMSE: 92.71 W/m² (irradiance); 0.616°C (temp); $5,250/year savings; 16.8 t CO_2/year	Deterministic simulation; geographic specificity; need BESS integration, stochastic modeling, real-time control
[79] 2026	ANN-based Incremental Conductance MPPT; dual control framework; hybrid microgrid PV + wind + nonlinear loads	98% power extraction; THD voltage: 12.50%→0.68%; THD current: 27.52%→1.71%	Simulation-only; computational demands; unaddressed operational factors; need hardware implementation, real-time testing, partial shading solutions, hybrid AI optimization; propose HIL Implementation
[80] 2025	100 kW DC PV (SunPower) + 100-200 kWh LiFePO4; 4 modes (PV Dominant, Hybrid, Grid-Dependent, V2G); CCCV strategy	Voltage ripple: ~2mV; 600 kWh/day; 109.5 t CO_2/year savings	Geographic specificity; cost variability; simplified battery modeling; no detailed power quality analysis; need adaptability, V2G integration, IoT and AI technologies
[81] 2024	Wavelet transform + FGSVM/WKNN; feature matrix 80,008×13; FRT factors (LVRT, HVRT) for GCPV fault detection	FGSVM: 94.9% accuracy; 99% True Positive Rate; WKNN faster training	Relies on training data; no aging impact on converters; simulation-only; narrow fault scope; need hybrid deep learning, transfer learning, XAI, digital twin, multi-sensor fusion, real-time applications
[82] 2026	XGBoost, GBR, PR across 4 Tunisian locations; tilt angle optimization; physics-based design integration	XGBoost R^2: 97.33%; tilt optimization: 2.95-3.259% energy improvement; annual solar energy:	Restricted site data; no economic/environmental assessments; simplified loss modeling; need

Ref	Methodology	Key Finding	Research Gap
		2,053-2,293 kWh/m²; 10-13 panels required	comprehensive evaluations and energy management innovations
[83] 2024	Station manager with 4 operating modes; state-space modeling; Process-in-the-Loop (PIL) on DSP hardware.	MPC outperforms PID/SMC; reduced IAE; seamless mode switching; protective measures; novel dynamic switching algorithm	No forecasting mechanisms; no field testing; high initial costs; model dependencies; need PV forecasting and broader grid support; propose Deep Learning + RL
[84] 2025	Virtual impedance + KNN regression; 7-state space model; Bode plot analysis; 1000 datasets; microgrid capacitor resonance analysis	R^2: 0.976 (KNN outperforms other regression); resonance at 4800/7030/9650 Hz; substantial THD reduction; stable during voltage sags	No hardware validation; no online learning; no scalability tests for multiple PV units; need hardware validation and online learning methods
[85] 2026	Enhanced droop control + virtual inertia/damping; attention-based DRL for grid impedance estimation; Texas Instruments DSP implementation	THD: 3.2%→1.8%; Settling time: 25ms→12ms; inference latency <50μs; real-time operation for weak grid scenarios	Complex architecture; extensive datasets needed; single inverter only; need formal stability proof, multi-inverter coordination, enhanced RL explainability
[86] 2025	FOPID + FLRNN + DSTATCOM + DTEO; DAHN architecture (3 layers); fractional calculus; 400V/50Hz grid, 5kW PV	IEEE-519 compliance; significantly reduced THD; superior memory; robust voltage regulation	High computational demands; complex architecture; no hardware validation; unresolved scalability and cybersecurity issues; need real-time implementation, large-scale deployment, EV charging integration
[87] 2024	5-layer Sugeno ANFIS MPPT (37.5kW PV) + Modified DTC with fractional PID tuning (40kW DFIG); multiple scenarios	73-94% tracking speed improvement (ANFIS); power gains; reduced fault currents; dual-resource optimization	Extensive ANFIS training; hardware complexity for PID; scalability limitations; limited fault types; need forecasting, enhanced control, hardware validation; propose CNN-LSTM-Attention + multi-agent learning
[88] 2025	DFSOF: 5 layers (Control Center, Evaluation Module); adaptive load forecasting + frequency deviation analysis + RL + real-time battery scheduling	Energy efficiency: 85.2%→96.4%; Frequency accuracy: 89.5%→94.2%; Response time: 10.5s→4.3s	Simulation-only validation; scalability issues; data quality dependence; need multi-agent EMS, V2G integration, real-time energy trading; propose Hybrid Deep RL Framework
[89] 2026	Unsupervised learning: K-means, GMM, AHC, DBSCAN; features: Self-Consumption Ratio, Grid Dependency Ratio; weather regression	4 optimal clusters; K-means validated against hierarchical; irradiance key influence; humidity significant for one cluster	Geographic and climatic constraints; need expanding system types, intraday dynamics, improved weather modeling; propose multi-site data collection and enhanced methodological tools

Ref	Methodology	Key Finding	Research Gap
[90] 2026	Improved MOPSO; grid-connected hybrid renewable microgrid (PV, wind, microturbine, diesel, BESS); multi-objective (cost, emissions, renewable use)	Cost reduction: up to 72.1%; Emissions: up to 22.4%; Renewable use: up to 46.6%; robust and computationally efficient	Deterministic model; missing intra-hour dynamics; scalability concerns; need probabilistic forecasting, stochastic controls, hybrid learning approaches
[91] 2026	EMS + NS with Raspberry Pi; linear programming; VDE-AR-N 4105 compliance	€0.91/day additional revenue; 92.8% energy autonomy; proactive grid compliance; innovative real-time protection	Relies on linear programming; deterministic models; no real grid testing; need Bayesian deep learning for uncertainty, grid-forming inverter technology, hybrid control strategies
[92] 2025	LR-XGBoost hybrid forecasting; SHAP framework; 8 adaptive rule-based EMS strategies prioritizing SHAP values	MSE: 416.63; RMSE: 20.41; MAE: 12.24; R^2: 0.9975; 4.5% grid import reduction; 97.4% self-consumption; 0.692s computation	Rule-based nature; no uncertainty quantification; single-location; fixed battery capacity; need Bayesian deep learning, multi-objective optimization, real-time control
[93] 2026	SAREM: Monte Carlo + HDS scenario reduction; weighted sum multi-objective; BESS (short-term) + HESS (long-term); GDPC/BPC resilience; IEEE-33/69	Cost reduction: 30.67-33.38%; 27% loss reduction; 50% resilience improvement; comprehensive uncertainty handling	MINLP computational complexity; scenario reduction fidelity loss; arbitrary weight selection; no real-world validation; GAMS dependency; simplified HESS (no degradation); need Bayesian deep learning, RL, Hybrid SAREM-RL Framework
[94] 2026	Rule-based EMS with priority-based control + degradation-aware decision-making; 3 configurations (Off-grid, Off-grid+V2H, On-grid); EV mobility profiles	96.4% renewable share (Off-grid+V2H); significant NPC and emission reductions; favorable socio-economic impacts	Rule-based reliance on fixed patterns; linear degradation assumptions; no predictive controls; need Bayesian deep learning, RL, grid-forming inverter technology, community collaboration, climate change impact assessments
[95] 2026	5-stage: FCM clustering + CNN feature extraction + WNN multi-scale + Informer transformer + WOA optimization; Monte Carlo Dropout uncertainty	R^2: 0.98; MAPE: 0.88%; outperforms LSTM; strong generalization; effective weather variability handling	High computational complexity; memory requirements; edge deployment challenges; need synchronized data, real-time forecasting; propose FCM + TFT + GNN + Bayesian Deep Learning + SAC
[96] 2025	HANNIS-PMS: 3-layer hierarchical (PI primary + ANN secondary + SoC-supervised ANN tertiary); dual-mode (grid-connected/islanded); batteries + supercapacitors	Voltage regulation: ±0.88V; Settling time: 10ms; virtually no overshoot; Phase margin >60°; THD <1%; excellent renewable capture	Simulation-only; no communication delay modeling; fixed ANN weights; no adaptability; need HIL testing, MPC integration, enhanced deep learning, Bayesian deep learning, digital twins, IoT deployment
[97] 2025	Federated deep MPC + SecureGraph-FedNet + Dynamic Stochastic Neuro-Evolution Optimizer; digital twin + multiagent learning	Energy efficiency: 98.52%; Security score: 0.99; Voltage stabilization: 0.5s; cybersecurity and privacy preservation	High computational complexity; no hardware deployment; synthetic dataset dependencies; limited privacy-preserving learning and decentralized intelligence; propose physics-informed digital twin + HIL validation

Ref	Methodology	Key Finding	Research Gap
[98] 2025	EP and O MPPT + EMS for power coordination; PV efficiency optimization	PV efficiency: 99.89%; THD: 14.09%→0.67%; mitigates voltage sag, swell, harmonics; robust under dynamic conditions	Parameter sensitivity; simplified battery modeling; control complexities; linearization assumptions; simulation-only; need Bayesian Deep Learning and RL for improvements
[99] 2026	LightGBM + SHAP-guided multi-objective framework; 9 dynamic control rules; optimization (cost, degradation, performance)	Total cost: 5.72 (vs 6.07 MILP, 8.01 MPC); weekly savings: 7.37; lowest battery cycles: 2.38	Data granularity issues; no uncertainty quantification; no disaggregated EV data; no RL integration; need Bayesian Deep Learning and RL for forecasting and rule discovery
[100] 2026	RF for PV forecasting (R^2=0.9994) + LR for load (R^2=1.000) + GA optimization; 1.0 kWp PV + 800 kWh battery + 3.6 kW inverter	Peak grid: 53.3% reduction; Grid dependency: 39.29%; Energy costs: 35.14% reduction	XGBoost underperformance; ANN complexities; geographic restrictions; no real-time deployment; need deep learning enhancements, RL, advanced MPC, innovative energy trading
[101] 2026	Adaptive fuzzy-shaped DDPG with GRU; SAM hybrid system; fuzzy logic for reward shaping (SoC + grid fluctuations); PV-fuel cell-battery	Operating cost: \$166.76→\$113.37; Grid variance: 2276.06→1267.98 kW^2; Hydrogen: 56.69→28.51 kg; 100% PV utilization; zero SoC violations	DDPG hyperparameter sensitivity; single-agent control; limited load/price forecasting; need multi-agent DRL, real-world deployment, digital twin integration, federated learning
[102] 2025	LEO + QCGNN; QZSI-based PV with battery; PI-FOPID hybrid controller; SPWM; bidirectional DC-DC converter	Power loss: 2W; THD: 5%; Testing time: 0.512 ms; robust under varying conditions	QCGNN black-box nature; relies on high-quality training data; simplified battery model; quantum computing scalability concerns; need XAI integration, real-world validation, broader renewable applications
[103] 2026	3-layer Hybrid AI (Data Ingestion/Normalization + AI Processing + Decision/Control); LLM Protocol Translator + LSTM/Transformers + RL (PPO); Edge-Cloud hybrid	TLR: 143.6% improvement; Cross-Protocol Sync Error: 75% reduction; RUSI: 270% enhancement; 53ms latency; 37% memory reduction (<1% accuracy loss)	Dataset limitations; LLM reliability; black-box interpretability; need real-world deployment, diverse training data; propose Quantum-Inspired Optimization + Green AI Score
[104] 2026	Hybrid WbOA–APINN; HESS (BESS + SC); Wind Turbine + PV modeling; multi-objective optimization	System efficiency: 98.7%; Operational cost: \$124.5/day; CO_2: 68 kg; significant statistical robustness	Computational time; fixed emission factors; no physical testbed validation; need demand response integration, operational aspect validation; propose Multi-Area Robust EMS Framework with degradation-aware optimization + real-time synchronization

4.1 Identified Research Gap

The reviewed literature indicates that existing energy management approaches address different aspects of grid-connected photovoltaic (PV) and battery energy storage systems (BESS), but their capabilities vary according to their objectives, system configurations, and operating conditions. Some

methods focus primarily on PV generation and load forecasting, whereas others emphasize energy scheduling, battery operation, economic optimization or grid stability. Although these approaches have contributed to improving individual aspects of energy management, their limitations highlight the need for a more coordinated framework that considers prediction uncertainty, adaptive decision-making, operational constraints, and grid-support requirements. Table 3 summarizes the principal strengths and limitations of the technology categories examined in this review.

Table 3. Research gaps identify from the literature review

Technology	Strength	Limitation
ANN/LSTM/CNN Forecasting	Good prediction accuracy	No uncertainty quantification
Fuzzy Logic EMS	Simple and robust	Rule-based, not adaptive
MPC	Excellent optimization	Sensitive to forecast errors
RL/DRL	Adaptive learning	Stability and safety concerns
Hybrid ML Methods	Accurate forecasting	No grid support
Battery Optimization	Battery constraint management	No frequency support
Grid Stability Methods	Frequency/voltage control	No intelligent EMS

The comparison highlights several interconnected research needs. First, forecasting models should provide information about predictive uncertainty, rather than relying exclusively on point predictions, so that subsequent scheduling decisions can account for variations in PV generation and load demand. Second, adaptive scheduling methods should be coordinated with explicit operational constraints to improve the feasibility and safety of battery charging, discharging, and grid power exchange. Third, battery degradation and state-of-health considerations should be incorporated into energy management objectives to balance short-term economic benefits against long-term battery performance. Finally, grid-support functions, including voltage and frequency regulation, should be considered alongside energy scheduling rather than evaluated solely as independent control tasks. These gaps motivate further investigation of an integrated energy management framework combining Bayesian Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) forecasting, Soft Actor-Critic (SAC) reinforcement learning, Stochastic Model Predictive Control (SMPC), and Virtual Synchronous Machine (VSM)-based grid-forming inverter control. Bayesian CNN–LSTM could estimate PV generation and load demand while quantifying predictive uncertainty. SAC could learn adaptive energy-scheduling policies, while SMPC could incorporate uncertainty scenarios and enforce defined operational constraints within a receding-horizon optimization process. Meanwhile, VSM-based grid-forming control could provide voltage and frequency support at the inverter-control level. The methods therefore address complementary functions within the proposed architecture. However, their combined effectiveness, computational feasibility, and ability to improve overall system performance must be established through simulation and comparative evaluation.

5 CONCLUSIONS

This review systematically examined energy management systems (EMS) for grid-connected photovoltaic (PV) and battery energy storage systems (BESS), using the PRISMA 2020 framework to assess studies published between 2021 and 2026. It addressed the challenges of PV variability, uncertain load demand, battery constraints, economic scheduling, and grid stability. The findings indicate that rule-based methods offer simplicity but limited adaptability, while conventional optimization depends on model accuracy and uncertainty handling. Machine learning and deep learning support forecasting, whereas reinforcement learning enables adaptive scheduling. However, forecasting accuracy alone cannot guarantee effective energy management, and battery health, operational constraints, and grid stability require coordinated consideration. The review highlights the potential of integrating Bayesian Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) forecasting, Soft Actor-Critic (SAC)

reinforcement learning, Stochastic Model Predictive Control (SMPC), and Virtual Synchronous Machine (VSM)-based grid-forming inverter control. These methods could respectively support uncertainty-aware forecasting, adaptive scheduling, constraint-aware optimization, and voltage and frequency regulation. Their combined effectiveness, however, requires systematic validation. Future research should evaluate probabilistic forecasting accuracy and uncertainty calibration, compare integrated EMS frameworks against established baselines, incorporate battery degradation and state-of-health constraints, and assess computational complexity and reinforcement-learning safety. Further investigations should examine grid-support performance using voltage deviations, frequency response, settling time, and harmonic distortion. Validation should progress from MATLAB/Simulink simulations to hardware-in-the-loop testing and, where feasible, experimental demonstrations. These directions provide a foundation for developing more adaptive, reliable, economically efficient, and grid-supportive PV–battery energy management systems.

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