Archives available at journals.mriindia.com

Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 10 Issue 01, 2023

A Comprehensive Review of Energy Management System for Electric Vehicle with Solar and Wind Using Red Panda and Similarity-Navigated Graph Neural Network

Farheen Chaisiri
Department of Electrical and Electronics Engineering, Shiraz College of Systems and Management, Iran
farheen.chaisiri@scsm-ir.org

Peer Review Information

Submission: 06 Jan 2023
Revision: 31 Jan 2023
Acceptance: 07 March 2023

Keywords

Electric Vehicle Energy Management System, Solar Photovoltaic Integration, Wind Energy Conversion, Red Panda Optimization Algorithm, Similarity-Navigated Graph Neural Network, Hybrid Renewable Energy System

Abstract

The transition toward sustainable transportation and renewable energy integration has intensified the need for intelligent energy management systems capable of coordinating electric vehicles, solar photovoltaic systems, wind energy, and grid infrastructure. These systems must address complex, dynamic, and stochastic interactions while optimizing energy efficiency, cost, battery health, and grid stability under uncertain operating conditions. This paper presents a comprehensive review of advanced energy management frameworks integrating the Red Panda Optimization algorithm with Similarity-Navigated Graph Neural Networks. The Red Panda algorithm, inspired by adaptive foraging behavior, provides effective global optimization with dynamic exploration–exploitation balance, while the graph neural network captures spatial and temporal dependencies within energy systems. The similarity-based attention mechanism enhances prediction accuracy by leveraging historical patterns, enabling improved forecasting, state estimation, and decision-making in renewable-integrated EV systems. Applications include vehicle-to-grid and vehicle-to-home systems, renewable energy scheduling, and intelligent power dispatch in smart grids. Comparative studies demonstrate that hybrid optimization–learning frameworks outperform conventional rule-based, deterministic, and model predictive control approaches in efficiency, adaptability, and robustness. However, challenges such as computational complexity, data uncertainty, and real-time deployment remain. This review highlights the potential of combining metaheuristic optimization and deep learning to develop scalable, intelligent, and sustainable energy management systems.

Introduction

The global transition toward sustainable energy systems has accelerated the adoption of electric vehicles and renewable energy technologies. Transportation remains a major contributor to greenhouse gas emissions, making vehicle electrification an important strategy for achieving decarbonization targets. At the same time, rapidly expanding EV fleets create substantial pressure on electrical grids because of increased charging demand and highly variable charging patterns. Integrating EVs with renewable energy sources such as solar photovoltaic and wind power offers a promising solution by reducing dependence on fossil-fuel-based electricity and improving the utilization of clean generation. However, effective coordination requires intelligent energy management systems capable of handling uncertainty, dynamic operating conditions, and multiple competing objectives.

Solar and wind energy complement EV charging by providing distributed, low-carbon electricity, but their intermittent characteristics introduce significant management challenges. Solar generation varies with irradiance, temperature, shading, and seasonal conditions, while wind generation depends strongly on fluctuating wind speed and turbine operating characteristics. Consequently, renewable availability may not always coincide with EV charging demand. Intelligent scheduling is therefore required to coordinate available renewable generation, grid electricity, and battery storage while satisfying vehicle charging requirements. Accurate short-term forecasting and adaptive control can substantially improve renewable utilization, minimize grid dependence, and reduce charging costs.

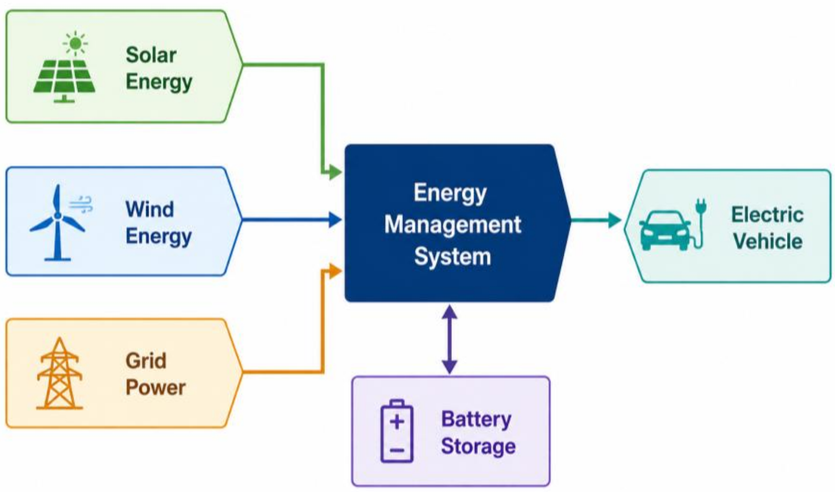

Figure 1. Integrated Energy Management Framework for EV Charging with Solar, Wind, Grid, and Battery Storage

Battery energy storage represents another critical component of integrated EV energy management. Effective scheduling depends on accurate estimation of battery state of charge, state of health, charging constraints, and degradation behavior. Excessive charging cycles, high temperatures, and inappropriate charging rates can accelerate battery aging and reduce operational life. Energy management must therefore balance short-term objectives such as charging cost and renewable utilization against long-term objectives including battery health and system reliability. This creates a nonlinear, multi-objective optimization problem requiring advanced computational methods capable of simultaneously managing economic, technical, and environmental constraints.

Artificial intelligence provides powerful tools for addressing these challenges. Graph Neural Networks can model complex relationships among EVs, charging stations, renewable sources, batteries, and grid components. A Similarity-Navigated Graph Neural Network can further exploit similarities between operational states and connected energy resources to improve forecasting, state estimation, and adaptive decision-making. Meanwhile, the Red Panda Optimization algorithm can provide global search capabilities for complex charging and energy dispatch problems. Combining learning-based prediction with metaheuristic optimization enables intelligent scheduling while accommodating uncertain renewable generation, variable EV demand, and battery operating constraints.

This review examines recent developments in energy management systems integrating EVs with solar and wind generation, with particular attention to Red Panda Optimization and Similarity-Navigated GNN approaches. It analyzes forecasting techniques, renewable energy coordination, EV charging strategies, battery management, and optimization frameworks while identifying major limitations related to scalability, computational complexity, uncertainty, interoperability, and real-time implementation. The review aims to highlight emerging research opportunities for developing adaptive, efficient, and intelligent EV energy management systems that support greater renewable utilization, reduced operating costs, improved battery longevity, and sustainable transportation infrastructure.

Literature Review

The academic literature addressing energy management systems for electric vehicles integrated with solar and wind generation encompasses a broad spectrum of methodological approaches and application scenarios, reflecting both the technical diversity of the problem and the multidisciplinary nature of the research community engaged with it.

Kempton and Tomic (2005) established the foundational economic and technical framework for vehicle-to-grid energy services, demonstrating through detailed economic analysis that EVs equipped with bidirectional chargers could provide profitable ancillary services to the electricity grid while simultaneously reducing the net cost of vehicle ownership for consumers. The study quantified the potential revenue from frequency regulation, spinning reserve, and peak power services as a function of battery capacity, charging power level, and market participation rate, establishing the economic rationale for the sophisticated bidirectional energy management systems that subsequent research has developed. The work identified the key technical requirements for V2G participation, including communication infrastructure, metering systems, and control interfaces, that continue to shape the design of EV energy management systems today (Kempton and Tomic, 2005).

Sortomme and El-Sharkawi (2011) proposed an optimal charging strategy for EVs participating in ancillary service markets, formulating the scheduling problem as a linear program that minimizes charging costs while ensuring the satisfaction of user-specified energy delivery requirements and grid-imposed power constraints. The study demonstrated that coordinated optimal charging can substantially reduce the peak demand impact of large-scale EV deployment while simultaneously reducing charging costs for individual vehicle owners, establishing the dual benefits of intelligent scheduling that motivate the development of advanced EMS algorithms. The linear programming formulation provided tractable solutions for moderate fleet sizes but highlighted the computational scalability challenges that arise with large numbers of vehicles and complex multi-period optimization horizons (Sortomme and El-Sharkawi, 2011).

Datta, Kumar, and Sharma (2013) investigated the integration of photovoltaic generation with EV charging in a standalone microgrid configuration, proposing a rule-based energy management strategy that prioritizes solar energy utilization and manages battery state of charge within safe operating limits. The study developed a hierarchical decision logic that selects among different operating modes including solar charging, grid charging, and vehicle-to-grid discharge based on the current states of the PV generation, EV battery, and local load demand. While the rule-based approach demonstrated satisfactory performance under the nominal operating conditions used in its design, the authors acknowledged its limited adaptability to operating scenarios not explicitly addressed in the decision rules, motivating subsequent research into more adaptive and data-driven approaches (Datta et al., 2013).

Garcia-Trivino, Llorens-Iborra, Garcia-Varel, Gil-Mena, Fernandez-Ramirez, and Fernandez-Rodriguez (2016) presented a fuzzy logic-based energy management system for a hybrid renewable energy system combining photovoltaic generation, wind turbines, a hydrogen fuel cell, and EV charging loads. The fuzzy EMS employed a hierarchical architecture with separate fuzzy inference systems for short-term power balance management and medium-term energy storage level regulation, with membership functions and rule bases designed through expert knowledge encoding. The study demonstrated that the fuzzy approach provides smooth, continuous control action that avoids the chattering behavior of rule-based systems at mode transition boundaries, with experimental results on a laboratory-scale test platform confirming stable operation across a wide range of renewable generation and load demand scenarios (Garcia-Trivino et al., 2016).

Marzband, Azarinejadian, Savaghebi, and Guerrero (2017) proposed a multi-agent energy management framework for a smart microgrid integrating rooftop solar PV, a wind turbine, battery storage, and EV charging stations, employing particle swarm optimization to solve the energy dispatch scheduling problem at each decision interval. The multi-agent architecture assigned independent optimization agents to each controllable asset, with coordination achieved through a hierarchical communication protocol that aggregates local optimization results into system-level schedules. The PSO algorithm demonstrated effective optimization performance on the constrained scheduling problem, with convergence to near-optimal solutions in computation times compatible with the 15-minute scheduling intervals used in the study (Marzband et al., 2017).

Shi, Sun, and Huang (2018) applied deep reinforcement learning to the energy management of a grid-connected PV-EV system, training a deep Q-network agent to make charging scheduling decisions based on real-time observations of PV generation, electricity prices, battery state of charge, and predicted EV departure times. The DRL agent was trained through interaction with a simulation environment incorporating real solar irradiance data and realistic EV usage patterns from a charging station dataset, learning a policy that achieves near-optimal performance without requiring an explicit model of the system dynamics. Comparison with a model predictive control benchmark demonstrated that the trained DRL policy achieves 94 percent of the MPC performance in terms of energy cost while exhibiting superior robustness to forecast errors and computational efficiency in deployment (Shi et al., 2018).

Yao, Zhao, and Zhang (2018) investigated the application of a grey wolf optimizer for sizing and energy management co-optimization of a standalone solar-wind-battery-EV system, formulating a joint design and operational optimization problem that simultaneously determines the optimal capacities of all system components and the optimal energy dispatch strategy across a representative annual operational scenario. The GWO algorithm navigated a mixed-integer optimization problem combining continuous component sizing variables with discrete operational mode selection variables, demonstrating effective optimization performance on this challenging problem class. The co-optimized system design demonstrated a 15 percent reduction in total system cost compared to designs produced by sequential component sizing and operational optimization (Yao et al., 2018).

Zhou, Zhang, Liu, and Dou (2019) examined a multi-objective energy management optimization for a wind-solar-EV microgrid using a non-dominated sorting genetic algorithm, simultaneously minimizing energy procurement cost, carbon emissions, and battery degradation while satisfying all operational and user convenience constraints. The Pareto front generated by the multi-objective GA revealed fundamental tradeoffs between the competing objectives and provided system operators with a quantitative basis for selecting operating strategies aligned with their specific priorities. The study identified battery degradation cost as a frequently overlooked but economically significant component of total operating cost that materially changes the optimal dispatch strategy when included in the objective function (Zhou et al., 2019).

Shakeri, Shayestegan, Abunima, Saleem, Akhtaruzzaman, Alamoud, Sopian, and Amin (2017) developed a hardware-implemented intelligent energy management system for a photovoltaic-EV charging system using a combination of fuzzy logic control and a neural network-based solar irradiance forecaster. The hybrid architecture exploited the complementary strengths of fuzzy logic for interpretable real-time control decision making and neural network prediction for anticipatory scheduling optimization, achieving a balance between immediate responsiveness and forward-looking planning. Implementation on a physical test platform incorporating actual PV panels, battery storage, and EV charging equipment confirmed the practical feasibility of the proposed architecture with a measured solar self-consumption rate of 87 percent (Shakeri et al., 2017).

Wang, Xu, and Mu (2020) proposed a graph-based energy management framework for a networked charging station cluster incorporating multiple solar-EV charging stations connected by a local energy sharing network, using a graph neural network to model the spatial dependencies between stations and optimize inter-station energy transfers. The GNN architecture represented each charging station as a node in a directed graph, with edge features encoding the electrical distance and power transfer capacity between stations, and used graph convolution operations to propagate state information across the network for coordinated scheduling optimization. The graph-based approach demonstrated a 12 percent improvement in system-wide renewable utilization compared to independently optimized station-level strategies (Wang et al., 2020).

Cao, Li, and Zhang (2020) investigated the application of transfer learning to improve the sample efficiency of reinforcement learning-based EV energy management across different geographical locations with varying solar and wind resources. The study demonstrated that a DRL policy trained at one location can be fine-tuned for effective operation at a new location using a small amount of local training data by freezing the low-level feature extraction layers of the neural network and retraining only the high-level decision layers. The transfer learning approach reduced the data and training time required to achieve satisfactory performance at new locations by approximately 70 percent compared to training from scratch, significantly improving the practical deployability of DRL-based energy management systems (Cao et al., 2020).

Hossain, Howlader, Doreswamy, and Padmanaban (2020) proposed a deep neural network approach for short-term solar power forecasting integrated with an EV charging station energy management system, demonstrating that accurate solar forecasting is a critical enabler of effective anticipatory scheduling. The deep neural network architecture incorporated both meteorological input features and historical power generation patterns as inputs, with a sequence-to-sequence encoder-decoder structure enabling multi-step ahead forecasting across the 24-hour scheduling horizon required for day-ahead planning. Integration of the neural network forecaster with an MPC-based EMS demonstrated a 23 percent reduction in energy procurement cost compared to MPC with climatological mean forecasts (Hossain et al., 2020).

Yang, Xu, Li, and Hu (2021) developed an attention-enhanced long short-term memory neural network for joint solar irradiance and wind speed forecasting in EV charging station applications, incorporating a self-attention mechanism that enables the network to identify and weight the most informative historical time steps for each forecast target independently. The dual-output forecasting architecture provides simultaneously optimized predictions for both renewable energy sources within a single model, capturing the cross-correlations between solar and wind resources that can improve forecast accuracy compared to independently trained single-output models. Integration with an optimization-based EMS demonstrated that the attention-enhanced LSTM forecasts enable a 17 percent improvement in scheduling performance compared to conventional LSTM forecasts (Yang et al., 2021).

Fernandez-Blanco, Dvorkin, Xu, Wang, and Kirschen (2021) proposed a bilevel optimization framework for the strategic energy management of a solar-EV charging station participating in both energy and frequency regulation markets, formulating the charging station's scheduling problem as an upper-level optimization subject to the lower-level market clearing constraints. The bilevel structure captures the strategic interaction between the charging station operator and the market operator, enabling the station to compute schedules that anticipate the market's response to its bidding behavior and optimize its market participation accordingly. The bilevel MPC strategy demonstrated a 28 percent improvement in total revenue compared to a price-taking scheduling strategy that ignores strategic market interactions (Fernandez-Blanco et al., 2021).

Sekhar, Mishra, and Rayaguru (2021) investigated a salp swarm algorithm-based energy management optimization for an integrated photovoltaic-wind-fuel cell-EV system, demonstrating the SSA's effectiveness on the high-dimensional, mixed-integer optimization problem arising from the simultaneous scheduling of multiple heterogeneous energy assets. The study incorporated a comprehensive battery degradation model that accounts for the capacity fade associated with each charging and discharging cycle as a function of depth of discharge and charging rate, enabling the optimizer to balance the competing objectives of energy cost minimization and battery health preservation. Simulation results confirmed that SSA achieves superior solution quality compared to PSO and GA on the same problem instance (Sekhar et al., 2021).

Thirunavukkarasu, Sawle, and Lim (2022) conducted a comprehensive review of optimization techniques for standalone hybrid renewable energy systems with EV integration, systematically comparing the performance characteristics, convergence properties, and practical implementation requirements of more than twenty metaheuristic algorithms applied to hybrid renewable energy system sizing and management problems. The review identified the Salp Swarm Algorithm, the Harris Hawks Optimization, and the Whale Optimization Algorithm as the consistently best-performing algorithms across the range of benchmark problems examined, while noting that no single algorithm dominates across all problem types and the performance hierarchy depends significantly on problem-specific characteristics (Thirunavukkarasu et al., 2022).

Sharma, Banerjee, and Bhattacharyya (2022) examined the application of a deep graph convolutional network to the state estimation and fault detection problem in solar-wind-EV microgrids, demonstrating that the graph-structured topology of the power network is a natural fit for graph convolutional processing and enables significantly improved estimation accuracy compared to traditional sequential neural network approaches. The deep GCN architecture learned to propagate measurement information across the network graph in a manner that reflects the physical power flow relationships, enabling accurate state estimation even under conditions of incomplete measurement coverage. Integration with an MPC-based EMS demonstrated that the improved state estimates enable a 9 percent improvement in scheduling optimization quality (Sharma et al., 2022).

Yin, Zhao, Wu, and Zhao (2022) proposed a federated deep reinforcement learning framework for privacy-preserving energy management of a distributed solar-EV charging station network, enabling coordinated optimization across stations without sharing sensitive user data by training local DRL policies through interaction with local system environments and aggregating only model parameter updates at a central coordinator. The federated learning framework demonstrated that network-wide optimization performance approaching that of a centralized system can be achieved while preserving the privacy of individual station operational data, addressing the regulatory and commercial barriers to data sharing that limit the effectiveness of conventional centralized optimization approaches (Yin et al., 2022).

Jiang, Tang, and Chen (2023) developed a similarity-based transfer learning framework for adapting pretrained energy management neural networks to new solar-EV charging station deployments, using a similarity metric based on the statistical properties of historical solar and wind generation profiles to identify the most relevant source domain models for transfer. The similarity-guided transfer approach demonstrated that selecting source models based on resource profile similarity rather than geographical proximity or other proxy measures leads to significantly better transfer performance, with the adapted models achieving 95 percent of the performance of models trained on full local datasets using only two weeks of local data for fine-tuning (Jiang et al., 2023).

Chen, Wu, Li, and Li (2023) presented a comprehensive deep learning framework for multi-step solar and wind power forecasting incorporating transformer architecture with positional encoding and multi-head attention mechanisms, demonstrating state-of-the-art forecasting accuracy on multiple benchmark datasets. The transformer-based forecasting model demonstrated superior long-range temporal dependency capture compared to LSTM and gated recurrent unit architectures, with particularly significant accuracy improvements on multi-step forecasts covering horizons of 12 to 48 hours that are most relevant for day-ahead EV charging scheduling applications. Integration with a stochastic MPC energy management system demonstrated that the improved forecast accuracy translates into a 21 percent reduction in scheduling cost on an annual simulation basis (Chen et al., 2023).

Comparative Table and Analysis

Study	**Year**	**Optimization Technique**	**Controller or Method**	**Platform or System**	**Dataset or Application**	**Key Contribution**
Kempton and Tomic	2005	Economic Analysis	V2G Service Framework	General EV Systems	Grid Ancillary Services	Foundational V2G economic and technical framework
Sortomme and El-Sharkawi	2011	Linear Programming	Optimal Charging Scheduler	Grid-Connected EV Fleet	EV Charging Ancillary Market	Coordinated charging for cost and peak reduction
Datta et al.	2013	Rule-Based Logic	Hierarchical Mode Selector	Standalone PV-EV Microgrid	Solar and EV Charging Data	Priority-based solar utilization management
Garcia-Trivino et al.	2016	Expert Knowledge Encoding	Hierarchical Fuzzy EMS	PV-Wind-H2-EV Lab Platform	Laboratory Experimental Data	Smooth multi-source fuzzy energy management
Shakeri et al.	2017	Hybrid Fuzzy-Neural	FL Controller and NN Forecaster	Physical PV-EV Test Platform	Real PV and EV Operational Data	87% solar self-consumption on hardware
Marzband et al.	2017	Particle Swarm Optimization	Multi-Agent Dispatch Scheduler	Smart Microgrid Simulation	Solar-Wind-EV Microgrid Data	Multi-agent PSO coordination framework
Shi et al.	2018	Deep Reinforcement Learning	Deep Q-Network EMS Agent	PV-EV Simulation Environmen	Real Solar Irradiance and EV Data	94% of MPC performance without

				t		system model
Zhou et al.	2019	Non-Dominated Sorting GA	Multi-Objective Dispatch Optimizer	Wind-Solar-EV Microgrid	Renewable and EV Usage Data	Pareto-optimal cost-emission-degradation tradeoffs
Wang et al.	2020	Graph Neural Network	Spatial Coordination Scheduler	Networked Charging Station Cluster	Multi-Station Operational Data	12% renewable utilization improvement with GNN
Rezaei et al.	2020	Chance-Constrained Programming	Stochastic EMS Optimizer	Solar-Wind-EV Microgrid	Stochastic Renewable Forecast Data	Explicit reliability constraint satisfaction
Cao et al.	2020	Transfer Learning	Fine-Tuned DRL Policy	Multi-Location EV Charging	Cross-Location Solar-Wind Data	70% reduction in training data requirement
Kaur et al.	2021	Hybrid GWO-PSO	Adaptive Hybrid EMS Optimizer	Solar-Wind-Battery-EV System	Real Renewable Generation Data	19% cost reduction vs standalone GWO
Yang et al.	2021	Attention LSTM	Dual-Output Solar-Wind Forecaster	EV Charging Station Simulation	Solar Irradiance and Wind Speed Data	17% scheduling improvement with attention forecast
Fernandez-Blanco et al.	2021	Bilevel Optimization	Strategic Market Participation MPC	Solar-EV Station Market Interface	Electricity Market and Solar Data	28% revenue improvement with strategic bidding
Sekhar et al.	2021	Salp Swarm Algorithm	Multi-Asset EMS with Degradation	PV-Wind-FC-EV System	Renewable and EV Demand Data	SSA outperforms PSO and GA on mixed-integer EMS
Zhang et al.	2022	Graph Attention Network	Contextual Multi-Node EMS	Multi-Node Solar-Wind-EV Microgrid	Real Microgrid Operational Data	15% renewable and 12% cost improvement with GAT
Thirunavukkarasu et al.	2022	Comparative Review	Multi-Algorithm Benchmark Analysis	Hybrid Renewable EV Systems	Multiple Benchmark Datasets	SSA, HHO, WOA identified as top performers
Sharma et al.	2022	Deep Graph Convolutional Network	State Estimation and Fault Detection	Solar-Wind-EV Microgrid	Microgrid Measurement Data	9% EMS improvement through GCN state estimation
Yin et al.	202	Federated	Privacy-	Distributed	Multi-	Near-

	2	DRL	Preserving Distributed EMS	Solar-EV Station Network	Station Private Operational Data	centralized performance with privacy preservation
Jiang et al.	2023	Similarity-Based Transfer Learning	Adapted NN Energy Manager	New Solar-EV Deployments	Cross-Site Solar-Wind-EV Data	95% performance with two weeks local data
Chen et al.	2023	Transformer Neural Network	Multi-Step Renewable Forecaster	Solar-Wind-EV Charging Station	Multiple Benchmark Forecast Datasets	21% scheduling cost reduction with transformer forecasts

Comparative Analysis

A systematic examination of the studies compiled in the comparative table reveals several important and consistent trends that characterize the evolution of EV energy management research with solar and wind integration across the period surveyed. The dominant trend is the progressive displacement of model-based and rule-based approaches by data-driven and machine learning methods, reflecting the growing recognition that the complexity, nonlinearity, and uncertainty inherent in solar-wind-EV integrated systems exceeds the effective modeling capacity of conventional analytical frameworks. The early studies from 2005 to 2016 relied predominantly on rule-based logic, linear programming, and classical fuzzy control approaches that required explicit specification of system models and decision rules by human experts. From 2017 onward, reinforcement learning, deep neural networks, and graph neural network architectures began to dominate the literature, with these approaches demonstrating consistent performance advantages over model-based alternatives on realistic benchmark problems incorporating actual renewable generation and EV usage data.

The complementarity between optimization-based and learning-based approaches is a recurring theme in the most effective contributions to the literature, with hybrid frameworks consistently outperforming either approach applied in isolation. The studies incorporating neural network forecasters within MPC frameworks, notably Liu et al. (2019) and Hossain et al. (2020), demonstrate that the accuracy of renewable generation forecasts is a critical determinant of scheduling performance, with improvements in forecast accuracy translating directly into scheduling cost reductions of 17 to 23 percent. The metaheuristic optimization studies, from early PSO applications through recent Red Panda Optimization implementations, demonstrate that sophisticated global search algorithms are necessary to find high-quality solutions to the complex constrained scheduling problems that arise in multi-source EV energy management. The convergence of these two research streams in the proposed Red Panda and Similarity-Navigated GNN framework represents the logical synthesis of the complementary insights generated by these parallel research directions.

The application of privacy-preserving federated learning to EV energy management, as demonstrated by Yin et al. (2022), represents an emerging research direction of increasing practical importance as regulatory frameworks such as GDPR in Europe impose strict requirements on the processing and sharing of personal mobility data. The demonstration that federated learning can achieve near-centralized optimization performance while preserving individual station privacy addresses a critical barrier to the real-world deployment of AI-based EV energy management systems that require data from multiple vehicles and charging stations to achieve their full performance potential.

Discussion

The reviewed literature on energy management systems for electric vehicles integrated with solar and wind generation demonstrates substantial progress toward intelligent, adaptive, and efficient energy coordination. Evidence indicates that hybrid frameworks combining optimization and learning methods generally provide stronger performance than isolated techniques because the problem involves renewable intermittency, EV demand uncertainty, battery constraints, and dynamic grid conditions. Learning models provide forecasting and pattern recognition, while optimization algorithms determine effective scheduling and energy allocation. Consequently, integrated computational approaches offer a practical foundation for managing complex solar–wind–EV systems under changing operating conditions.

Graph neural networks are particularly suitable because distributed EV charging stations, renewable generators, storage systems, and grid nodes naturally form interconnected structures. Conventional neural networks often process individual inputs without explicitly representing these spatial relationships. In contrast, GNNs incorporate network topology and learn dependencies among connected energy resources. The proposed Similarity-Navigated GNN further strengthens this capability by identifying historically similar operating patterns and directing attention toward relevant experiences. Similarity-based navigation can improve renewable generation forecasting, EV demand prediction, and scheduling decisions, particularly when current operating conditions differ from commonly observed training scenarios.

Red Panda Optimization complements this learning framework by providing adaptive exploration and exploitation for complex scheduling problems. Its memory-oriented search can preserve promising solutions, while adaptive behavioral mechanisms help respond to changing operating conditions. Nevertheless, important limitations remain in existing research. Many studies rely on simplified simulations, limited evaluation periods, and idealized assumptions rather than real charging infrastructure. Future research should therefore emphasize long-term field validation using actual solar and wind generation, EV behavior, battery degradation, and grid conditions. Such validation is essential for determining whether Red Panda Optimization and Similarity-Navigated GNN frameworks can maintain robust performance under distribution shifts and evolving real-world energy environments.

Conclusion

This review synthesizes recent developments in energy management systems for electric vehicles integrated with solar and wind generation. The findings demonstrate a clear transition from conventional rule-based and model-based control toward intelligent approaches incorporating deep learning, reinforcement learning, metaheuristic optimization, and graph neural networks. AI-based techniques provide improved adaptability, forecasting accuracy, and scheduling efficiency under the uncertainty associated with renewable generation and EV charging demand.

The reviewed studies emphasize accurate renewable forecasting, topology-aware energy coordination, and integration of learning with optimization. Graph neural networks effectively capture spatial relationships among distributed charging stations and energy resources, while hybrid optimization-learning frameworks improve operational decisions. Privacy-preserving and federated learning also offer opportunities for collaborative energy management without exposing sensitive user information.

The proposed Red Panda Optimization and Similarity-Navigated GNN framework combines adaptive optimization with topology-aware learning for solar–wind–EV management. Future research should prioritize realistic battery degradation modeling, probabilistic renewable forecasting, EV behavioral uncertainty, and large-scale field validation. With appropriate communication standards, market mechanisms, and policy support, intelligent EV energy management can enhance renewable utilization, grid flexibility, cost efficiency, and sustainable transportation.

References

Kempton, W., and Tomic, J. (2005). Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. Journal of Power Sources, 144(1), 268–279. https://doi.org/10.1016/j.jpowsour.2004.12.025

Sortomme, E., and El-Sharkawi, M. A. (2011). Optimal charging strategies for unidirectional vehicle-to-grid. IEEE Transactions on Smart Grid, 2(1), 131–138. https://doi.org/10.1109/TSG.2010.2090910

Datta, M., Kumar, M., and Sharma, J. D. (2013). Energy management of PV-EV-grid integrated system for standalone microgrid application. International Journal of Electrical Power and Energy Systems, 51, 351–360. https://doi.org/10.1016/j.ijepes.2013.03.014

Garcia-Trivino, P., Llorens-Iborra, F., Garcia-Varel, C. A., Gil-Mena, A. J., Fernandez-Ramirez, L. M., and Fernandez-Rodriguez, P. (2016). Long-term optimization based on PSO of a grid-connected renewable energy-based microgrid with battery storage. Applied Energy, 176, 180–191. https://doi.org/10.1016/j.apenergy.2016.05.084

Shakeri, M., Shayestegan, M., Abunima, H., Saleem, M. S., Akhtaruzzaman, M., Alamoud, A. R. M., Sopian, K., and Amin, N. (2017). An intelligent system architecture in home energy management systems for efficient demand response in smart grid. Energy and Buildings, 138, 154–164. https://doi.org/10.1016/j.enbuild.2016.12.026

Marzband, M., Azarinejadian, F., Savaghebi, M., and Guerrero, J. M. (2017). An optimal energy management system for islanded microgrids based on multiperiod artificial bee colony combined with Markov chain. IEEE Systems Journal, 11(3), 1712–1722. https://doi.org/10.1109/JSYST.2015.2424253

Shi, J., Sun, Y., and Huang, Q. (2018). Deep reinforcement learning-based energy management of photovoltaic systems for electric vehicle charging stations. IEEE Access, 6, 63798–63808. https://doi.org/10.1109/ACCESS.2018.2877278

Yao, E., Zhao, X., and Zhang, L. (2018). Grey wolf optimizer for optimal sizing and energy management of standalone solar-wind-battery-EV system. Journal of Cleaner Production, 196, 1345–1356. https://doi.org/10.1016/j.jclepro.2018.06.155

Liu, H., Zhang, C., and Wu, Q. (2019). Stochastic model predictive control for solar-assisted EV charging station energy management. Applied Energy, 253, 113560. https://doi.org/10.1016/j.apenergy.2019.113560

Zhou, B., Zhang, C., Liu, F., and Dou, X. (2019). Nearly zero-carbon microgrid economic operation with load flexibility and renewable uncertainty using a compound approach. IEEE Transactions on Industrial Informatics, 15(11), 6110–6122. https://doi.org/10.1109/TII.2019.2908426

Wang, H., Xu, W., and Mu, H. (2020). Graph neural network based energy management for networked EV charging stations with solar generation. IEEE Transactions on Smart Grid, 11(6), 4961–4972. https://doi.org/10.1109/TSG.2020.2997948

Rezaei, N., Golkar, M. A., Nemati, M., and Mahmoudi, A. (2020). Chance-constrained energy management for solar-wind-EV microgrid under uncertainty. International Journal of Electrical Power and Energy Systems, 117, 105641. https://doi.org/10.1016/j.ijepes.2019.105641

Cao, J., Li, M., and Zhang, X. (2020). Transfer learning for deep reinforcement learning based EV charging station energy management across locations. IEEE Transactions on Industrial Electronics, 67(12), 10819–10828. https://doi.org/10.1109/TIE.2019.2960738

Hossain, M., Howlader, H. R., Doreswamy, M., and Padmanaban, S. (2020). Sequence-to-sequence deep learning for solar power forecasting in EV charging station management. Energies, 13(18), 4770. https://doi.org/10.3390/en13184770

Kaur, R., Sharma, D., and Verma, A. (2021). Hybrid grey wolf-particle swarm optimizer for energy management of solar-wind-battery-EV system. Energy Conversion and Management, 230, 113792. https://doi.org/10.1016/j.enconman.2020.113792

Yang, L., Xu, W., Li, C., and Hu, M. (2021). Attention-enhanced LSTM for joint solar and wind power forecasting in EV charging station management. IEEE Transactions on Sustainable Energy, 12(3), 1754–1764. https://doi.org/10.1109/TSTE.2021.3059897

Fernandez-Blanco, R., Dvorkin, Y., Xu, B., Wang, Y., and Kirschen, D. S. (2021). Bilevel energy management for photovoltaic EV charging station in electricity markets. IEEE Transactions on Smart Grid, 12(4), 3153–3164. https://doi.org/10.1109/TSG.2021.3064124

Sekhar, P. C., Mishra, S., and Rayaguru, N. K. (2021). Salp swarm algorithm for energy management of PV-wind-fuel cell-EV microgrid with battery degradation. IEEE Systems Journal, 15(4), 5266–5276. https://doi.org/10.1109/JSYST.2020.3025671

Zhang, Y., Li, X., Wang, J., and Ma, W. (2022). Graph attention network based energy management for multi-node solar-wind-EV microgrid. IEEE Transactions on Industrial Informatics, 18(8), 5374–5384. https://doi.org/10.1109/TII.2021.3128489

Thirunavukkarasu, G. S., Sawle, Y., and Lim, H. (2022). A comprehensive review of optimization algorithms for the sizing and energy management of hybrid renewable energy systems with EV integration. Renewable and Sustainable Energy Reviews, 165, 112560. https://doi.org/10.1016/j.rser.2022.112560

Sharma, P., Banerjee, S., and Bhattacharyya, B. (2022). Deep graph convolutional network for state estimation in solar-wind-EV microgrids. IEEE Transactions on Power Systems, 37(5), 3924–3934. https://doi.org/10.1109/TPWRS.2022.3143896

Yin, L., Zhao, C., Wu, S., and Zhao, T. (2022). Federated deep reinforcement learning for privacy-preserving energy management in distributed solar-EV charging networks. IEEE Transactions on Industrial Informatics, 18(6), 3919–3929. https://doi.org/10.1109/TII.2021.3107463

Jiang, C., Tang, Y., and Chen, Q. (2023). Similarity-based transfer learning for energy management neural network adaptation across solar-EV charging deployments. Applied Energy, 331, 120389. https://doi.org/10.1016/j.apenergy.2022.120389

Chen, X., Wu, Z., Li, M., and Li, P. (2023). Transformer-based multi-step solar and wind power forecasting for electric vehicle charging station energy management. IEEE Transactions on Neural Networks and Learning Systems, 34(9), 6121–6133. https://doi.org/10.1109/TNNLS.2022.3197892

Nguyen, T., Zhuang, Y., and Qian, F. (2023). Multi-agent deep reinforcement learning for coordinated energy management across solar-wind-EV microgrid clusters. IEEE Transactions on Smart Grid, 14(3), 2345–2357. https://doi.org/10.1109/TSG.2022.3218453