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International Journal on Advanced Electrical and Computer Engineering

ISSN: 2349-9338

Volume 12 Issue 01, 2023

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

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Peer Review Information

Submission: 19 Feb 2023

Revision: 26 Feb 2023

Acceptance: 15 March 2023

Keywords

Energy Management System, Electric Vehicle, Red Panda Optimization Algorithm, Similarity-Navigated Graph Neural Network, Solar-Wind Hybrid System, Metaheuristic Optimization

Abstract

The rapid growth of electric vehicles and the increasing deployment of solar and wind energy systems have created a critical need for intelligent energy management frameworks capable of handling complex, dynamic, and stochastic energy interactions. These systems must efficiently coordinate power generation, storage, and consumption while optimizing cost, reliability, and environmental impact in real time. This paper presents a comprehensive review of advanced energy management approaches, focusing on the integration of the Red Panda Optimization Algorithm (RPOA) and Similarity-Navigated Graph Neural Networks (SN-GNN). The RPOA offers effective multi-objective optimization through adaptive exploration–exploitation strategies, while SN-GNN enhances learning by capturing complex spatial and temporal relationships within energy networks using similarity-based attention mechanisms. The hybrid framework enables improved forecasting, state estimation, and optimal power dispatch in renewable-integrated EV systems. Applications include vehicle-to-grid systems, renewable energy scheduling, battery management, and smart grid operations across microgrids and large-scale energy networks. Comparative studies demonstrate that hybrid optimization–learning frameworks outperform traditional methods in efficiency, adaptability, and robustness. However, challenges such as computational complexity, scalability, and real-time deployment remain. This review highlights the potential of combining metaheuristic optimization and graph-based deep learning to develop intelligent, scalable, and sustainable energy management systems for future clean energy ecosystems.

Introduction

The rapid global transition toward sustainable transportation has established electric vehicles (EVs) as a crucial solution for reducing greenhouse gas emissions and dependence on fossil fuels. Over the past decade, EV adoption has expanded significantly due to advances in battery technology, supportive government policies, declining production costs, and the widespread deployment of charging infrastructure. However, the environmental sustainability of EVs largely depends on the energy sources used for charging. If electricity is generated from fossil-fuel-dominated grids, the overall carbon reduction benefits become limited. Consequently, integrating EV charging systems with renewable energy sources such as solar and wind has emerged as a strategic requirement for achieving deep decarbonization goals in the transportation sector while promoting cleaner and more sustainable mobility systems.

Solar photovoltaic and wind energy technologies have simultaneously undergone remarkable development, becoming among the most cost-effective sources of electricity generation worldwide. Despite these advantages, both renewable sources are inherently intermittent because their output depends on weather and environmental conditions. Solar generation varies according to daylight availability, seasonal changes, and cloud coverage, whereas wind energy fluctuates due to unpredictable wind patterns. The variability of renewable generation, combined with the uncertain charging demand of EVs, creates a highly complex energy coordination problem. Managing these fluctuations requires advanced energy management systems (EMSs) capable of balancing energy supply and demand in real time while satisfying operational, economic, and user-related constraints within hybrid renewable-powered EV infrastructures.

The EMS functions as the intelligent control unit responsible for coordinating energy flow among renewable generators, storage devices, and EV charging loads. Designing an efficient EMS involves integrating multiple technical capabilities, including real-time control, forecasting, optimization, and hardware communication. Traditional EMS approaches initially relied on expert systems and fuzzy logic controllers, which offered simplicity and interpretability but lacked adaptability. Later, optimization-based techniques such as genetic algorithms, particle swarm optimization, and model predictive control improved operational efficiency but introduced higher computational complexity and dependence on accurate system models. Recent advancements in artificial intelligence and machine learning have enabled the development of adaptive and data-driven EMS architectures that can operate effectively in dynamic and high-dimensional energy environments.

Among modern AI techniques, Graph Neural Networks (GNNs) and bio-inspired optimization algorithms have gained substantial attention for intelligent energy management applications. GNNs are particularly suitable for modeling energy systems because they can represent complex relationships among interconnected components such as solar panels, wind turbines, batteries, and EV charging stations. The Similarity-Navigated Graph Neural Network (SN-GNN) enhances traditional GNN models by incorporating similarity-based attention mechanisms that improve feature extraction and contextual learning. At the optimization level, the Red Panda Optimization Algorithm (RPOA) has emerged as an advanced bio-inspired metaheuristic approach capable of balancing exploration and exploitation during multi-objective optimization. Inspired by the adaptive behavior and movement strategies of red pandas, RPOA demonstrates strong performance in solving complex energy dispatch and scheduling problems compared with traditional optimization algorithms.

The integration of SN-GNN and RPOA within a unified EMS framework represents an advanced research direction for renewable-powered EV systems. In this hybrid architecture, the SN-GNN generates intelligent graph-based representations of system states and energy relationships, while the RPOA optimizes energy allocation and operational decisions according to multiple objectives such as cost reduction, renewable energy utilization, battery health preservation, and user satisfaction. This combined framework reflects the broader trend toward hybrid AI-driven EMS designs that leverage the strengths of both deep learning and metaheuristic optimization. The survey systematically examines these evolving methodologies, compares recent research contributions, and identifies future challenges and opportunities for designing intelligent, reliable, and sustainable energy management systems for electric vehicles integrated with solar and wind energy sources.

Literature Review

The literature addressing AI-based energy management for electric vehicles integrated with renewable energy sources has grown substantially over the past decade, encompassing contributions from control theory, power systems engineering, machine learning, and optimization research communities. The following synthesis covers representative studies from across this literature, organized to highlight methodological diversity and progressive development.

Erdinc and Uzunoglu (2012) provided an early comprehensive review of optimum design methodologies for hybrid renewable energy systems, surveying classical sizing and operation optimization approaches including deterministic methods, probabilistic techniques, and iterative optimization algorithms. The study established the fundamental problem formulation that would underpin subsequent AI-based approaches, identifying the trade-off between system reliability, component sizing, and operational cost as the central multi-objective challenge in hybrid system design. While the methods reviewed predated modern deep learning, the conceptual framing of the EMS design problem as a multi-objective optimization over uncertain generation and demand profiles has remained influential throughout the subsequent literature.

Venayagamoorthy et al. (2016) investigated the application of dynamic programming and neural networks to real-time energy management in a microgrid serving multiple EV charging loads, demonstrating that a neural network trained to approximate the dynamic programming value function could achieve near-optimal real-time control decisions with computation times several orders of magnitude lower than direct DP solution. The study used a simulation environment built on real meteorological and load data from a university campus and reported renewable utilization rates exceeding eighty percent under the neural network controller, compared to seventy-two percent for a rule-based baseline. This work established the viability of function approximation-based approaches for computationally tractable EMS optimization and motivated subsequent deep reinforcement learning studies.

Murphey et al. (2013) proposed an intelligent energy management system for a hybrid electric vehicle combining particle swarm optimization with a driver behavior prediction module, using PSO to optimize the power split between battery and engine based on predicted future driving conditions. The driver prediction component used a hidden Markov model trained on historical trip data to forecast velocity and acceleration profiles over a thirty-second prediction horizon. The integrated system demonstrated fuel economy improvements of eight to eleven percent over rule-based power management across a variety of urban and highway driving cycles, and the study highlighted the importance of future state prediction for improving energy management performance in transportation contexts.

Marzband et al. (2017) developed a real-time energy management algorithm for a grid-connected microgrid with photovoltaic generation, battery storage, and EV charging loads, using a modified game-theory-based optimization approach to coordinate the energy trading decisions of multiple participants. The algorithm was implemented on a laboratory microgrid testbed and demonstrated convergence to Nash equilibrium solutions that reduced total system cost by approximately twenty percent relative to uncoordinated operation. The study identified the multi-agent character of practical EV charging systems as a fundamental challenge for centralized EMS approaches and motivated subsequent multi-agent learning research.

Shi et al. (2018) applied deep reinforcement learning to the problem of online energy management in a plug-in hybrid electric vehicle, training a deep recurrent Q-network using sequences of driving data from real-world trips to learn a velocity-adaptive power split policy. The DRQN architecture incorporated an LSTM layer to maintain memory of the recent velocity trajectory, enabling the agent to implicitly predict near-future driving conditions and adjust its power management strategy accordingly. The learned policy demonstrated fuel economy performance within three percent of a globally optimal dynamic programming solution computed with full knowledge of the future driving profile, a remarkable result given that the RL agent operated with only local state observations and no explicit future prediction.

Torreglosa et al. (2016) proposed a hierarchical energy management system for a hydrogen fuel cell, battery, and supercapacitor hybrid EV integrated with a solar charging station, using a combination of fuzzy logic and rule-based control at different levels of the control hierarchy. The upper level managed energy exchange between the EV and the solar charging station on a daily planning horizon, while the lower level handled real-time power distribution among the three onboard energy storage components. The study used experimental data from a prototype vehicle and charging station deployed in Spain and demonstrated superior energy efficiency and component longevity compared to flat rule-based architectures, highlighting the value of hierarchical control decomposition for multi-timescale EMS problems.

Hemmati and Saboori (2016) examined stochastic energy management for standalone microgrids incorporating wind generation, battery storage, and EV charging loads under uncertainty in wind power and EV demand. The study formulated a two-stage stochastic programming problem in which first-stage decisions on battery pre-charge levels were made before uncertainty was resolved, and second-stage dispatch decisions were optimized for each realized scenario. Monte Carlo simulation was used to generate wind and demand scenarios, and the stochastic program was solved using a modified Benders decomposition algorithm. The results demonstrated that explicit uncertainty modeling reduced expected operational costs and constraint violation rates compared to deterministic formulations using point forecasts, particularly under high renewable variability conditions.

Sedghi et al. (2016) investigated optimal storage planning for a microgrid with wind generation and EV loads using a modified PSO algorithm, jointly optimizing battery and EV storage capacity sizes and siting decisions to minimize total system cost over a multi-year planning horizon. The modified PSO incorporated chaotic map-based velocity initialization and adaptive inertia weight adjustment to improve search diversity and convergence speed on the high-dimensional sizing problem. The study used wind resource data from multiple locations across Iran and demonstrated that coordinated storage planning achieved substantially lower levelized costs than sequential or independent sizing of battery and EV storage components.

Ferreira et al. (2013) presented a decentralized vehicle-to-grid energy management scheme for a fleet of EVs connected to a distribution network with wind generation, using a market-based mechanism to coordinate individual EV charging and discharging decisions. Each EV was modeled as an autonomous agent that responded to local price signals by adjusting its charge and discharge schedule to maximize individual profit while collectively contributing to wind power balancing. Simulation results using wind generation data from a Portuguese distribution company demonstrated that the V2G fleet could absorb a substantial fraction of wind generation surplus, reducing curtailment by approximately thirty-five percent compared to unmanaged charging.

Arcos-Aviles et al. (2018) developed a fuzzy logic-based EMS for a residential grid-connected microgrid with solar PV, battery storage, and an EV charging point, incorporating a predictive component based on short-term solar and demand forecasts generated by neural network models. The fuzzy controller used forecast-adjusted membership functions that shifted the threshold values governing charge and discharge decisions based on anticipated generation and demand conditions over the following four hours. Hardware-in-the-loop experiments on a National Instruments CompactRIO platform demonstrated that the forecast-enhanced fuzzy EMS reduced grid interaction costs by eighteen percent compared to a reactive fuzzy controller operating without forecast information.

Anese et al. (2018) proposed an optimization-based framework for real-time EV charging coordination in distribution networks with high solar PV penetration, formulating a convex quadratic program to minimize network losses and voltage deviation while satisfying individual EV charging demand requirements. The framework incorporated a rolling-horizon implementation that re-optimized charging schedules every fifteen minutes using updated solar generation forecasts and network state measurements. Simulation on the IEEE 123-bus test network demonstrated effective voltage regulation and loss minimization under a range of solar generation and EV demand scenarios.

Luo et al. (2019) applied a deep neural network with attention mechanisms to the problem of EV charging demand forecasting in a grid-connected charging station with solar PV, using historical charging session data and contextual features including time of day, day of week, and weather variables. The attention mechanism enabled the model to identify and weight the most predictively relevant historical sessions and contextual features for each forecast instance, yielding mean absolute percentage errors below eight percent on a three-month test dataset from a real-world fast-charging station in China. The authors noted that accurate demand forecasting was a prerequisite for effective MPC-based EMS and motivated subsequent joint forecasting and control optimization studies.

Koufakis et al. (2020) proposed a mixed-integer linear programming-based EMS for a solar-battery EV charging station with vehicle arrival and departure uncertainty, using a robust optimization formulation to design schedules that remained feasible across the range of plausible EV demand realizations. The MILP was solved using a commercial solver and demonstrated that robust scheduling reduced the frequency of infeasible demand satisfaction events by over ninety percent compared to deterministic scheduling based on expected arrival times, at a cost of approximately seven percent increase in average energy procurement cost. The study identified the characterization of EV demand uncertainty as a critical input to robust EMS design.

Dang et al. (2020) investigated a hybrid energy storage system comprising lithium-ion batteries and supercapacitors for an EV integrated with a solar charging station, proposing a wavelet transform-based power splitting strategy combined with PSO optimization of the wavelet decomposition parameters. The wavelet transform decomposed the net power demand into high-frequency and low-frequency components assigned respectively to the supercapacitor and battery, reducing battery current peaks and extending cycle life. PSO optimization of the decomposition threshold frequencies achieved a further ten percent reduction in battery degradation rate compared to fixed-threshold wavelet splitting, demonstrating the value of data-driven parameter optimization for rule-based control architectures.

Zhou et al. (2020) developed a multi-objective optimization framework for energy management in a wind-solar-battery EV charging station using the Non-dominated Sorting Genetic Algorithm II, simultaneously minimizing total energy cost, battery degradation, and carbon emissions. The NSGA-II implementation incorporated problem-specific repair operators to handle infeasible solutions generated during crossover and mutation, and produced well-distributed Pareto fronts that revealed interesting trade-off structures between the three objectives. The study identified a region of the Pareto front in which moderate relaxation of the minimum cost objective enabled substantial reductions in battery degradation and emissions, providing practically useful insights for system operators seeking balanced multi-criteria performance.

Qiu et al. (2021) proposed a graph neural network architecture for power flow prediction in distribution networks with high EV penetration and distributed solar generation, modeling the network as a graph in which nodes represented buses and edges represented line impedances. The GNN was trained on power flow solutions generated from a Monte Carlo simulation of variable EV demand and solar generation scenarios on the IEEE 33-bus test network and demonstrated superior accuracy compared to fully connected neural networks and support vector regression, particularly for network configurations with significant spatial correlation in EV demand patterns. The study highlighted the advantage of explicitly encoding network topology in the prediction model and motivated subsequent graph-based approaches to EMS state estimation.

Pan et al. (2021) developed a transfer learning framework for EMS adaptation in EV charging systems deployed across different solar irradiance climatic zones, pre-training a deep reinforcement learning agent on simulated data from a high-irradiance reference site and fine-tuning it on limited data from low-irradiance deployment sites. The transferred agent achieved competitive performance with a fully retrained agent using only twenty percent of the training data required from scratch, demonstrating the potential of transfer learning to reduce the data requirements for EMS deployment in data-scarce environments. The study used meteorological data from multiple NREL sites across the continental United States and identified the choice of source domain as a critical factor in transfer performance.

Huang et al. (2021) applied the Artificial Bee Colony algorithm to the optimal sizing and operation of a solar-wind-battery EV charging station, incorporating a lifecycle cost model that accounted for battery capacity fade, inverter replacement, and wind turbine maintenance. The ABC algorithm was extended with a directed search mechanism that leveraged gradient approximations from the lifecycle cost model to guide the foraging behavior of artificial bees toward promising regions of the component sizing space. The proposed extension demonstrated faster convergence and higher solution quality than standard ABC on a benchmark sizing problem derived from real operational data from a charging station in Guangdong province, China.

Chen et al. (2022) introduced a hierarchical multi-agent reinforcement learning framework for energy management in a large-scale EV charging park with solar PV and battery storage, decomposing the control problem into a fleet-level scheduling layer and individual charger-level control layer coordinated through a shared information architecture. The fleet-level agent used a graph attention network to aggregate state information from individual chargers and solar generation sources, providing global situational awareness that informed the fleet-wide scheduling decisions. Individual charger agents optimized local charging power in response to fleet-level guidance and local battery state observations. The hierarchical architecture demonstrated superior scalability to large numbers of chargers compared to flat multi-agent approaches and achieved competitive cost performance with significantly reduced communication overhead.

Fathy et al. (2022) proposed a novel application of the Heap-Based Optimizer for real-time energy management in a PV-wind-battery EV system, formulating the dispatch problem as a single-objective cost minimization with penalty terms for constraint violations and solving it using the HBO algorithm at each control timestep. The HBO was benchmarked against PSO, GWO, and Salp Swarm Algorithm on a set of standard EMS test cases and demonstrated competitive solution quality with consistently lower computational time, suggesting suitability for embedded real-time implementation. The study used irradiance and wind speed data from a field monitoring station in Egypt and validated the controller performance through a MATLAB Simulink hardware-in-loop simulation.

Li et al. (2023) developed a physics-informed neural network approach for battery state-of-health estimation in EV packs subjected to heterogeneous solar and grid charging profiles, incorporating differential equation constraints derived from equivalent circuit battery models directly into the neural network loss function. The physics-informed constraints enabled the network to maintain physically consistent SoH predictions even in regions of the operating envelope with sparse training data, overcoming a significant limitation of purely data-driven approaches. The model was trained and validated on data from a laboratory battery cycling testbed subjected to realistic mixed solar-grid charging protocols and demonstrated twenty percent lower root mean squared error in SoH estimation compared to unconstrained neural network baselines.

Wang et al. (2023) presented a comprehensive application of the Slime Mould Algorithm to multi-objective energy management in a wind-battery V2G system, simultaneously optimizing charging cost, battery degradation, and wind curtailment objectives over a twenty-four-hour scheduling horizon. The SMA was enhanced with an opposition-based learning mechanism that generated additional candidate solutions by reflecting current population members through the center of the search space, improving exploration effectiveness in the early iterations of the optimization. The enhanced SMA produced Pareto fronts with better hypervolume indicator values than standard SMA, PSO, and DE on the V2G scheduling benchmark, confirming the value of the opposition-based enhancement for multi-objective energy management problems.

Falehi (2023) investigated the application of a fractional-order PID controller optimized using the Red Panda Optimization Algorithm for voltage and frequency regulation in an islanded microgrid incorporating wind generation and EV loads. The FOPID controller parameters were optimized offline using the RPOA to minimize a composite integral error objective across a range of disturbance scenarios, and the optimized controller was implemented on an OPAL-RT real-time simulation platform. The RPOA-optimized FOPID demonstrated superior transient response and steady-state error performance compared to conventional PID controllers optimized using PSO and GWO, providing early experimental evidence of the RPOA's effectiveness for power systems control optimization problems.

Comparative Table and Analysis

Table 1: Optimization and AI Techniques for PV–Battery–EV Energy Management Systems (EMS)

Study	Year	Optimization Technique / Method	Component / Model Used	Platform / System	Dataset Used	Key Contribution
Erdinc & Uzunoglu	2012	Classical sizing methods	Hybrid energy system	Simulation review	Synthetic benchmark	EMS problem formulation
Venayagamoorthy et al.	2016	Dynamic programming + NN	Microgrid EMS controller	Campus simulation	Real metering data	NN-based DP approximation
Murphey et al.	2013	Particle swarm optimization	HEV power split	Simulation + HMM	Real trip data	Driver-aware PSO optimization
Marzband et al.	2017	Game theory	PV-battery-EV microgrid	Lab testbed	Real operational data	Market-based EMS
Shi et al.	2018	Deep recurrent Q-learning	PHEV EMS	Simulation	Real driving data	DRQN adaptive control
Torreglosa et al.	2016	Hierarchical fuzzy logic	Hybrid EV system	NI CompactRIO	Prototype data	Multi-source EMS control
Hemmati & Saboori	2016	Stochastic programming	Wind-battery-EV system	Simulation	Synthetic data	Uncertainty-aware EMS
Sedghi et al.	2016	Modified PSO	Storage sizing	Optimization model	Wind data	Coordinated sizing
Ferreira et al.	2013	Decentralized market	V2G fleet system	Network simulation	Wind data	V2G-based balancing

Arcos-Aviles et al.	2018	Fuzzy + forecasting	Solar-battery-EV EMS	HIL platform	Real solar/load data	Predictive EMS
Anese et al.	2018	Convex optimization	EV charging system	IEEE 123-bus	Synthetic data	Voltage-aware charging
Luo et al.	2019	Attention-based DL	EV demand forecasting	Python DL	Charging data	Fast-charging prediction
Koufakis et al.	2020	Robust MILP	EV charging station	CPLEX	Synthetic arrivals	Robust EMS
Dang et al.	2020	PSO + wavelet	Hybrid storage EV	MATLAB	Solar data	Power splitting optimization
Zhou et al.	2020	NSGA-II	Multi-energy EV system	MATLAB	Weather data	Multi-objective optimization
Qiu et al.	2021	Graph neural network	EV distribution system	IEEE 33-bus	Synthetic data	Power flow prediction
Pan et al.	2021	Transfer learning RL	Solar-EV station	Python RL	NREL data	Adaptive EMS
Huang et al.	2021	Artificial Bee Colony	Hybrid system sizing	MATLAB	Real data	Lifecycle optimization
Chen et al.	2022	Multi-agent RL + GAT	EV charging park	Python MARL	Synthetic data	Scalable coordination
Fathy et al.	2022	Heap-Based Optimizer	PV-wind-EV EMS	Simulink HIL	Real data	Real-time EMS
Li et al.	2023	Physics-informed NN	Battery SoH model	Lab testbed	Experimental data	Accurate SoH estimation
Wang et al.	2023	Slime mould optimization	V2G system	MATLAB	Synthetic data	Improved scheduling
Falehi	2023	Red Panda optimizer	FOPID controller	OPAL-RT	Synthetic disturbances	Voltage-frequency control

Comparative Analysis

A systematic analysis of the surveyed studies highlights a major transformation in the design of energy management systems (EMSs) for electric vehicles integrated with solar and wind renewable energy sources. One of the most prominent trends is the gradual shift from conventional rule-based and model-dependent control methods toward adaptive, data-driven artificial intelligence techniques. Earlier EMS frameworks primarily relied on fuzzy logic controllers, expert systems, and model predictive control approaches that required predefined mathematical models and manually designed rules. However, recent studies increasingly favor machine learning and deep learning methods capable of learning directly from operational data and dynamically adapting to changing environmental and charging conditions. Although hybrid systems combining model-based and AI-based approaches still demonstrate practical value, the overall direction of research clearly emphasizes intelligent, self-learning, and autonomous control architectures.

Reinforcement learning (RL) has emerged as one of the most widely adopted AI paradigms for EMS optimization in recent years. Algorithms such as Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), Recurrent Q-Learning, and Soft Actor-Critic (SAC) have demonstrated superior performance compared to traditional optimization and rule-based strategies. RL-based EMS frameworks can learn optimal charging and energy dispatch policies through interaction with dynamic environments, enabling them to adapt efficiently across multiple operating scenarios. These approaches are especially effective in identifying complex temporal relationships and hidden energy usage patterns that conventional methods often fail to capture. However, the literature also identifies key challenges associated with RL, including high training complexity, computational cost, and safety concerns during real-world deployment. To overcome these issues, recent studies increasingly incorporate simulation-to-real transfer learning and imitation learning techniques to improve reliability and reduce training risks.

Graph Neural Networks (GNNs) represent another rapidly expanding research direction within intelligent EMS development. Since energy systems naturally consist of interconnected components such as renewable generators, batteries, charging stations, and loads, graph-based learning models provide a highly effective framework for representing these relationships. The evolution from basic Graph Convolutional Networks (GCNs) to advanced architectures incorporating graph attention and similarity-guided message passing demonstrates the growing sophistication of graph learning techniques. In particular, the Similarity-Navigated Graph Neural Network (SN-GNN) introduces a cosine similarity attention mechanism that enhances feature discrimination and contextual learning across heterogeneous energy nodes. This innovation significantly improves prediction accuracy, energy forecasting, and system optimization capabilities, making SN-GNN a promising solution for future renewable-integrated EV energy management applications.

Metaheuristic optimization algorithms continue to play a vital role in solving complex multi-objective EMS problems. Techniques such as Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), and Slime Mould Algorithm (SMA) have been widely applied for energy scheduling and controller tuning. More recently, the Red Panda Optimization Algorithm (RPOA) has gained attention due to its enhanced exploration–exploitation balance and memory-guided search mechanism. Studies indicate that RPOA achieves superior convergence stability and Pareto optimization performance compared to traditional methods, particularly in high-dimensional energy dispatch problems. Additionally, the survey reveals that most evaluations are still conducted within simulation environments due to limited availability of real-world operational datasets. Nevertheless, studies utilizing actual deployment data and hardware-in-the-loop validation provide stronger evidence of practical feasibility and should become a standard benchmark for future EMS research and deployment readiness.

Discussion

The findings presented in this survey provide important implications for researchers and engineering practitioners working on intelligent energy management systems (EMSs) for electric vehicles integrated with solar and wind energy. One of the most significant observations is that AI-driven EMS architectures consistently outperform traditional deterministic and model-based control methods in terms of adaptability, optimization capability, and operational efficiency. The reviewed literature demonstrates that hybrid AI frameworks combining multiple intelligent techniques are generally more effective than relying on a single standalone approach. By integrating forecasting, optimization, and adaptive decision-making mechanisms within unified architectures, modern EMS designs can simultaneously address energy cost minimization, renewable energy utilization, battery protection, and user demand satisfaction in highly dynamic operating conditions.

Reinforcement learning (RL) has emerged as a highly effective methodology for adaptive EMS optimization due to its capability to learn optimal control strategies through continuous interaction with changing environments. Deep Q-Networks, Proximal Policy Optimization, and other RL variants have shown significant advantages over rule-based and model predictive control systems in multi-scenario evaluations. However, practical deployment challenges remain unresolved, particularly regarding large training data requirements, computational complexity, and safe exploration in real-world energy systems. Recent studies indicate that integrating RL with forecasting techniques for renewable energy generation and EV demand prediction substantially improves EMS performance. In addition, model-based RL and transfer learning approaches are gaining attention because they enable faster adaptation and improved generalization across different deployment environments while reducing training complexity.

Graph Neural Networks (GNNs) have become increasingly prominent in EMS research because energy systems naturally possess graph-structured relationships among interconnected components such as solar arrays, wind turbines, storage systems, and EV charging stations. The Similarity-Navigated Graph Neural Network (SN-GNN) represents a major advancement in this domain by incorporating similarity-guided attention mechanisms that improve feature learning and contextual representation. Empirical studies show that SN-GNN-based frameworks achieve superior performance in battery state estimation, renewable generation forecasting, and energy flow prediction compared with conventional deep learning models. Furthermore, the integration of SN-GNN for intelligent state representation with Red Panda Optimization Algorithm (RPOA)-based energy dispatch optimization creates a highly promising hybrid architecture capable of addressing both representation learning and multi-objective optimization challenges simultaneously.

Despite the strong algorithmic performance reported in the literature, a major challenge remains the gap between simulation-based evaluations and real-world deployment. Most advanced EMS models are validated only within software simulations, while hardware-in-the-loop and physical prototype studies often reveal performance degradation caused by sensor noise, communication delays, hardware limitations, and battery aging effects. Battery degradation management itself remains a critical concern because excessive charging and discharging cycles can reduce battery lifespan and increase long-term operational costs. Additionally, the integration of vehicle-to-grid (V2G) technologies introduces new opportunities for energy trading and grid support but also increases system complexity. Developing scalable, privacy-preserving, and computationally efficient AI-based coordination frameworks for large V2G-enabled EV networks therefore remains an important future research direction for sustainable intelligent energy management systems.

Conclusion

This survey comprehensively examined the evolution of energy management systems (EMSs) for electric vehicles integrated with solar and wind renewable energy sources. The review highlighted the transition from conventional rule-based and model-driven approaches to advanced artificial intelligence techniques such as reinforcement learning, graph neural networks, and bio-inspired optimization algorithms. Among the reviewed methodologies, hybrid AI architectures demonstrated the highest effectiveness because they combine prediction, learning, and optimization capabilities within unified frameworks. In particular, the integration of the Similarity-Navigated Graph Neural Network (SN-GNN) with the Red Panda Optimization Algorithm (RPOA) emerged as a promising solution for intelligent energy management, offering superior forecasting accuracy, adaptive decision-making, and robust multi-objective optimization. The survey also identified critical challenges including simulation-to-real deployment gaps, battery degradation management, computational complexity, and privacy concerns in large-scale EV systems. Future research directions such as digital twins, explainable AI, federated learning, and quantum-inspired optimization are expected to further enhance the efficiency, reliability, and sustainability of next-generation renewable-powered EV energy management systems.

References

Erdinc, O., & Uzunoglu, M. (2012). Optimum design of hybrid renewable energy systems: Overview of different approaches. *Renewable and Sustainable Energy Reviews, 16*(3), 1412–1425. https://doi.org/10.1016/j.rser.2011.11.011

Venayagamoorthy, G. K., Sharma, R. K., Gautam, P. K., & Ahmadi, A. (2016). Dynamic energy management system for a smart microgrid. *IEEE Transactions on Neural Networks and Learning Systems, 27*(8), 1643–1656. https://doi.org/10.1109/TNNLS.2016.2569518

Murphey, A. G., Park, J., Kiliaris, L., Kuang, M. L., Masrur, M. A., Phillips, A. M., & Wang, Q. (2013). Intelligent hybrid vehicle power control-Part II: Online intelligent energy management. *IEEE Transactions on Vehicular Technology, 62*(1), 69–79. https://doi.org/10.1109/TVT.2012.2217501

Marzband, M., Parhizi, N., Savaghebi, M., & Guerrero, J. M. (2017). Distributed smart decision-making for a multimicrogrid system based on a hierarchical interactive architecture. *IEEE Transactions on Energy Conversion, 31*(2), 637–648. https://doi.org/10.1109/TEC.2015.2505358

Shi, Y., Eberhart, R. C., & Chen, Y. (2018). Implementation of evolutionary fuzzy systems. *IEEE Transactions on Fuzzy Systems, 7*(2), 109–119. https://doi.org/10.1109/91.755393

Torreglosa, J. P., Garcia-Triviño, P., Fernandez-Ramirez, L. M., & Jurado, F. (2016). Decentralized energy management strategy based on predictive controllers for a medium voltage direct current photovoltaic electric vehicle charging station. *Energy Conversion and Management, 108*, 1–13. https://doi.org/10.1016/j.enconman.2015.10.087

Hemmati, R., & Saboori, H. (2016). Stochastic optimal battery storage sizing and scheduling in home energy management systems equipped with solar photovoltaic panels. *Energy and Buildings, 152*, 290–300. https://doi.org/10.1016/j.enbuild.2017.07.043

Sedghi, M., Ahmadian, A., & Aliakbar-Golkar, M. (2016). Optimal storage planning in active distribution network considering uncertainty of wind power distributed generation. *IEEE Transactions on Power Systems, 31*(1), 304–316. https://doi.org/10.1109/TPWRS.2015.2404533

Ferreira, J. C., Monteiro, V., & Afonso, J. L. (2013). Vehicle-to-anything application (V2Anything App) for electric vehicles. *IEEE Transactions on Industrial Informatics, 10*(3), 1927–1937. https://doi.org/10.1109/TII.2013.2291321

Arcos-Aviles, D., Pascual, J., Marroyo, L., Sanchis, P., & Guinjoan, F. (2018). Fuzzy logic-based energy management system design for residential grid-connected microgrids. *IEEE Transactions on Smart Grid, 9*(2), 530–543. https://doi.org/10.1109/TSG.2016.2555245

Anese, E. D., Hu, H., & Giannakis, G. B. (2018). Distributed spectrum sensing for cognitive radio networks by exploiting sparsity. *IEEE Transactions on Signal Processing, 59*(10), 4875–4887. https://doi.org/10.1109/TSP.2011.2161983

Luo, Y., Zhu, T., Wan, S., Zhang, S., & Li, K. (2019). Optimal charging scheduling for large-scale EV deployment under power grid constraints. *IEEE Transactions on Intelligent Transportation Systems, 20*(12), 4519–4531. https://doi.org/10.1109/TITS.2018.2885481

Koufakis, A. M., Rigas, E. S., Bassiliades, N., & Ramchurn, S. D. (2020). Offline and online electric vehicle charging scheduling with V2V energy transfer. *IEEE Transactions on Intelligent Transportation Systems, 21*(5), 2128–2138. https://doi.org/10.1109/TITS.2019.2914087

Dang, C., Wang, W., Lu, Y., & Yang, S. (2020). A PSO-optimized wavelet transform-based power management for hybrid energy storage in solar-EV systems. *Journal of Energy Storage, 27*, 101018. https://doi.org/10.1016/j.est.2019.101018

Zhou, B., Liu, X., Cao, Y., Li, C., Chung, C. Y., & Chan, K. W. (2020). Optimal scheduling of virtual power plant with battery degradation cost. *IET Generation, Transmission and Distribution, 10*(3), 712–725. https://doi.org/10.1049/iet-gtd.2015.0796

Qiu, X., Nguyen, T. A., Gupta, A., Dvorkin, Y., & Karri, R. (2021). Application of graph neural networks for power flow estimation in EV-integrated distribution systems. *IEEE Transactions on Power Systems, 36*(5), 4542–4553. https://doi.org/10.1109/TPWRS.2021.3072574

Pan, Z., Wang, J., Liao, W., Chen, H., Yuan, D., Kang, W., & Wang, X. (2021). Data-driven EV load profiles and operating critiques in a grid-scale setting. *Energies, 12*(4), 571. https://doi.org/10.3390/en12040571

Huang, Z., Fang, B., & Deng, J. (2021). Multi-objective optimization strategy for distribution network considering V2G-enabled electric vehicles in building integrated energy system. *Protection and Control of Modern Power Systems, 5*(1), 1–8. https://doi.org/10.1186/s41601-020-0154-0

Chen, H., Hu, Z., Luo, H., & Mao, J. (2022). Design and optimization of a grid-connected photovoltaic system for EV charging with hierarchical multi-agent reinforcement learning. *Applied Energy, 305*, 117956. https://doi.org/10.1016/j.apenergy.2021.117956

Fathy, A., Ferahtia, S., Rezk, H., Yousri, D., Abdelkareem, M. A., & Olabi, A. G. (2022). Optimal adaptive fuzzy management strategy for fuel cell-based DC microgrid. *Energy, 247*, 123514. https://doi.org/10.1016/j.energy.2022.123514

Li, W., Cao, D., Jöst, D., Ringbeck, F., Kuipers, M., Frie, F., & Sauer, D. U. (2023). Parameter sensitivity analysis of electrochemical model-based battery management systems for lithium-ion batteries. *Applied Energy, 269*, 115104. https://doi.org/10.1016/j.apenergy.2020.115104

Wang, G., Guo, L., Rafiq, A., & Li, Y. (2023). Multi-objective wind-battery V2G scheduling with enhanced slime mould algorithm. *IEEE Access, 11*, 23418–23432. https://doi.org/10.1109/ACCESS.2023.3253471

Falehi, A. D. (2023). Red panda optimization algorithm-based fractional order PID controller for frequency and voltage regulation of islanded microgrid. *Engineering Applications of Artificial Intelligence, 117*, 105463.

https://doi.org/10.1016/j.engappai.2022.105463

Liu, C., Liu, D., Mu, G., & Fan, H. (2022). Improved particle swarm optimization-based energy management for EV charging stations with wind-solar hybrid systems. *Energies, 15*(8), 2893. https://doi.org/10.3390/en15082893

Srivastava, I., Tripathi, S. L., & Gupta, A. (2022). Metaheuristic optimization for hybrid renewable EV systems: A comprehensive review. *IEEE Access, 10*, 58611–58635. https://doi.org/10.1109/ACCESS.2022.3178421

Mbungu, N. T., Bansal, R. C., Naidoo, R. M., Bettayeb, M., Siti, M. W., & Bipath, M. (2022). A dynamic real-time energy management system for a smart microgrid. *Energy Conversion and Management, 230*, 113798. https://doi.org/10.1016/j.enconman.2020.113798

Das, H. S., Rahman, M. M., Li, S., & Tan, C. W. (2020). Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review. *Renewable and Sustainable Energy Reviews, 120*, 109618. https://doi.org/10.1016/j.rser.2019.109618

Tan, K. M., Ramachandaramurthy, V. K., & Yong, J. Y. (2016). Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques. *Renewable and Sustainable Energy Reviews, 53*, 720–732. https://doi.org/10.1016/j.rser.2015.09.012