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Artificial Intelligence Techniques for Energy Management System for Electric Vehicle with Solar and Wind Using Red Panda and Similarity-Navigated Graph Neural Network: Trends and Challenges

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Abstract

The global transition toward sustainable energy systems and electric mobility has created a critical need for intelligent energy management systems capable of coordinating electric vehicles with solar and wind energy sources. The intermittent nature of renewable energy and the dynamic behavior of electric vehicle demand introduce complex, nonlinear, and stochastic challenges that require advanced computational frameworks beyond conventional methods. This paper presents a comprehensive review of artificial intelligence-based energy management approaches, focusing on the integration of the Red Panda Optimization Algorithm (RPOA) and Similarity-Navigated Graph Neural Networks (SN-GNN). The RPOA provides efficient multi-objective optimization through adaptive exploration–exploitation strategies, while SN-GNN captures complex spatial and temporal dependencies within energy networks using similarity-based attention mechanisms. Together, they form a hybrid framework capable of accurate 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. Comparative analysis shows that hybrid optimization–learning frameworks outperform traditional techniques in efficiency, adaptability, and robustness. However, challenges such as computational complexity, scalability, and real-time implementation 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 next-generation electric transportation.

Introduction

The accelerating deployment of electric vehicles (EVs) across global transportation systems represents a major technological transformation of the twenty-first century, driven by environmental regulations, declining battery costs, and increasing awareness of fossil fuel impacts. EVs play a crucial role in decarbonizing transportation, which is a significant contributor to global greenhouse gas emissions. However, their sustainability benefits are fully realized only when powered by renewable energy sources. This necessity has intensified research into hybrid renewable energy systems that integrate solar photovoltaic and wind energy with energy storage units to support EV charging demands. Consequently, the integration of renewable energy with electrified transport has emerged as a multidisciplinary field involving power electronics, control systems, and artificial intelligence.

A central component of such systems is the Energy Management System (EMS), which coordinates energy flow between renewable sources, storage devices, vehicle loads, and the grid. The EMS must dynamically optimize multiple conflicting objectives such as maximizing renewable utilization, maintaining battery health, meeting vehicle demand, reducing cost, and ensuring reliability under uncertain conditions. These objectives create a highly nonlinear, high-dimensional, and time-varying optimization problem. Traditional methods like proportional-integral-derivative control or linear programming are often inadequate in handling such complexity, particularly in real-world scenarios with fluctuating renewable generation and unpredictable load behavior.

To address these challenges, artificial intelligence techniques have been increasingly adopted for EMS design. Rule-based systems offer simplicity but lack adaptability, while fuzzy logic improves flexibility but depends heavily on expert-defined rules. Model predictive control provides better foresight but suffers from high computational complexity and reliance on accurate system models. Reinforcement learning introduces adaptive decision-making through interaction with the environment but faces challenges such as slow convergence, unsafe exploration, and poor sample efficiency. These limitations highlight the need for more robust, scalable, and adaptive AI frameworks for energy management in EV–renewable systems.

Metaheuristic optimization methods have therefore gained significant attention due to their ability to explore large solution spaces without gradient information. Techniques such as Genetic Algorithms, Particle Swarm Optimization, and Grey Wolf Optimizer have been widely applied in hybrid energy systems. However, they often suffer from premature convergence and parameter sensitivity. The Red Panda Optimization Algorithm (RPOA) addresses these issues by mimicking the territorial behavior and adaptive foraging patterns of red pandas. Its dual-phase mechanism enhances both exploration and exploitation, enabling improved convergence and solution diversity in complex EMS optimization problems.

In parallel, Graph Neural Networks (GNNs) have emerged as powerful tools for modeling interconnected energy systems. Unlike traditional neural networks, GNNs operate on graph-structured data, making them suitable for representing EV networks, renewable sources, and storage systems. The Similarity-Navigated Graph Neural Network (SN-GNN) enhances this capability by introducing similarity-based attention mechanisms that prioritize meaningful node interactions. When integrated, RPOA and SN-GNN form a hybrid EMS framework where SN-GNN provides structured system representation and RPOA performs optimized decision-making. This synergy enables adaptive, data-driven, and computationally efficient energy management for solar-wind-EV systems, supporting the broader transition toward intelligent and sustainable power networks.

Literature Review

The literature on AI-driven energy management systems (EMS) for electric vehicles integrated with renewable energy sources has grown rapidly over the past decade, reflecting the convergence of smart grid technologies, machine learning, and sustainable transportation systems. Research in this domain spans optimization theory, control systems, renewable energy integration, and advanced artificial intelligence techniques, collectively aiming to improve energy efficiency, reduce operational costs, and enhance system reliability. The following synthesis reviews approximately twenty-five representative studies, organized thematically to highlight methodological evolution from rule-based control systems to deep learning, graph neural networks, and hybrid AI-metaheuristic frameworks.

Early foundational work by Siano et al. (2014) introduced demand response strategies for EVs in smart grids, demonstrating that rule-based coordination of charging schedules could significantly reduce peak demand and operational costs in distribution systems. Although limited by its pre-deep-learning framework, the study established EV charging as a multi-objective optimization problem involving temporal, spatial, and economic constraints. It also emphasized the importance of forecasting renewable generation and load demand, which later became central to AI-driven EMS research. This early conceptualization laid the groundwork for integrating intelligence into energy scheduling systems.

Liu et al. (2018) advanced the field by introducing a deep reinforcement learning framework using a deep Q-network for hybrid electric vehicle energy management. The model optimized power split decisions between internal combustion engines and electric motors using real-world driving cycles, achieving up to 12% fuel efficiency improvement compared to rule-based methods. Importantly, this study demonstrated the feasibility of model-free learning for EMS without requiring explicit vehicle dynamics modeling, although challenges in stability and generalization were identified. Building on this direction, Zhang et al. (2019) extended deep reinforcement learning to grid-connected EV charging systems integrated with solar PV, formulating the problem as a Markov decision process solved using proximal policy optimization. Their results showed improved cost efficiency and solar utilization under variable irradiance conditions, highlighting the importance of state representation design in learning-based EMS frameworks.

Further advancements in multi-agent and predictive control systems were explored by Yin et al. (2020), who proposed a multi-agent reinforcement learning framework for microgrids comprising EV charging stations, solar, wind, and battery storage. The decentralized structure improved scalability and reduced communication overhead while maintaining strong performance in minimizing energy costs and peak demand. In parallel, Huang et al. (2020) integrated long short-term memory (LSTM) networks with model predictive control (MPC) to improve forecasting accuracy for solar and wind generation. Their LSTM-enhanced MPC significantly reduced constraint violations and improved renewable utilization, demonstrating the critical role of accurate forecasting in EMS optimization.

Hossain et al. (2021) introduced a fuzzy logic-based EMS for a standalone solar-wind-battery system powering EV charging stations in rural microgrids. While the system improved battery longevity and renewable penetration, it remained dependent on expert-defined membership functions and lacked adaptability to dynamic environmental conditions. In contrast, Wang et al. (2021) applied graph convolutional networks (GCNs) for lithium-ion battery state-of-charge estimation, modeling inter-cell dependencies as graph structures. This approach significantly improved estimation accuracy under aging and heterogeneous conditions, marking one of the earliest applications of graph-based learning in EV battery management systems.

Kumar et al. (2021) applied Particle Swarm Optimization (PSO) for multi-objective energy dispatch in hybrid solar-wind-battery systems, optimizing cost, battery degradation, and renewable curtailment. Although effective in identifying Pareto-optimal solutions, PSO exhibited limitations in convergence stability. Rezaei et al. (2022) addressed real-time control challenges by combining Grey Wolf Optimization with deep neural network forecasting for plug-in hybrid EV energy management. The hybrid framework improved convergence speed and solution quality, demonstrating the benefits of combining predictive learning with metaheuristic optimization for real-time EMS applications.

Chen et al. (2022) introduced transformer-based architectures for wind power forecasting in EV fleet management systems. Their model outperformed LSTM and GRU approaches in long-term forecasting accuracy, reducing grid dependency when integrated with MPC-based scheduling. Li et al. (2022) employed Whale Optimization Algorithm (WOA) for optimal sizing and operation of solar-wind-battery EV charging stations, demonstrating computational efficiency advantages over PSO and Genetic Algorithms. Mbungu et al. (2022) further evaluated MPC strategies and highlighted stochastic MPC as superior in handling uncertainty, though computationally expensive for real-time applications.

Patel et al. (2022) proposed a CNN-based EMS framework treating energy state data as image-like representations, achieving near-optimal control performance with very low latency suitable for embedded systems. Saleh et al. (2023) extended graph neural networks to fault detection in hybrid microgrids, demonstrating the ability of GNNs to capture structural dependencies across solar, wind, battery, and EV nodes with high accuracy and low false positives. Ahmad et al. (2023) introduced a multi-objective Moth-Flame Optimization approach for community-scale EV systems with vehicle-to-grid (V2G) integration, achieving reduced emissions and peak demand under real-world constraints.

Zhao et al. (2023) developed adaptive dynamic programming for fuel cell-battery-solar EV systems, using neural approximators to learn value functions for infinite-horizon control problems. Ibrahim et al. (2023) demonstrated the feasibility of standalone renewable microgrids for rural EV charging using HOMER Pro and genetic algorithms, highlighting battery sizing as a critical reliability factor. Nguyen et al. (2023) applied attention-based encoder-decoder networks for joint forecasting of solar irradiance and EV load demand, improving prediction accuracy by modeling interdependencies between supply and demand. Sharma et al. (2023) developed a soft actor-critic reinforcement learning EMS for wind-battery EV systems under dynamic pricing, achieving robust convergence and strong generalization under distributional shifts. Xu et al. (2024) proposed graph attention networks for spatio-temporal energy flow prediction in EV-integrated distribution systems, demonstrating superior accuracy in capturing cascading power dynamics across network nodes.

Chen et al. (2024) introduced the Similarity-Navigated Graph Neural Network (SN-GNN), incorporating cosine similarity-driven message passing to improve energy state prediction in EV systems. The model outperformed conventional GCN and GAT architectures in battery health estimation and renewable forecasting tasks due to its adaptive attention mechanism. Ali et al. (2024) applied the Red Panda Optimization Algorithm (RPOA) to multi-objective EMS problems, showing improved Pareto diversity and convergence behavior compared to PSO, GWO, and other swarm-based techniques, particularly in high-dimensional settings.

Finally, Singh et al. (2024) integrated vehicle-to-grid functionality into AI-based EMS frameworks using a hybrid GNN-genetic algorithm model, demonstrating improved economic returns for EV owners while maintaining battery health constraints. Collectively, these studies illustrate the rapid evolution of EMS research from rule-based and deterministic optimization approaches toward intelligent, adaptive, and data-driven systems.

In summary, the literature demonstrates a clear progression toward hybrid AI frameworks combining reinforcement learning, graph neural networks, transformer models, and metaheuristic optimization techniques. While significant progress has been made in forecasting accuracy, optimization efficiency, and system scalability, challenges remain in computational complexity, real-time deployment, and robustness under uncertain renewable conditions. The integration of Red Panda Optimization Algorithm with Similarity-Navigated Graph Neural Networks represents a promising direction, offering a balance between global optimization capability and deep relational learning for next-generation EV energy management systems.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Siano et al.	2014	Rule-based scheduling	Smart grid controller	Distribution network	Real grid data	EV demand response framework
Liu et al.	2018	Deep Q-Network (DQN)	Hybrid EV drivetrain	Simulation (EPA cycles)	EPA driving cycles	DRL for HEV power split
Zhang et al.	2019	Proximal Policy Optimization	Grid-connected PV-EV station	Python RL environment	California solar + price data	RL for solar self-consumption
Yin et al.	2020	Multi-agent RL (MAPPO)	Multi-EV charging points	Microgrid simulation	Synthetic multi-agent data	Scalable decentralized EMS
Huang et al.	2020	MPC + LSTM forecasting	Solar-wind-EV hybrid	MATLAB/Simulink	Coastal meteorological data	LSTM-enhanced MPC
Hossain et al.	2021	Fuzzy Logic Control	Solar-wind-battery station	MATLAB simulation	Bangladesh weather data	Fuzzy EMS for rural charging
Wang et al.	2021	Graph Convolutional Network	Li-ion battery pack	Laboratory battery testbed	Battery cycling experiments	GCN for SoC estimation
Kumar et al.	2021	Particle Swarm Optimization	Solar-wind-battery EV	MATLAB optimization	NASA meteorological archives	PSO multi-objective dispatch
Rezaei et al.	2022	Grey Wolf Optimizer + DNN	PHEV with rooftop solar	dSPACE HIL platform	Real driving + irradiance data	Hybrid GWO-DNN EMS
Chen et	202	Transformer	Wind-EV	Python deep	NREL wind	Transformer

al.	2	attention	fleet management	learning	dataset	for wind forecasting
Li et al.	2022	Whale Optimization Algorithm	Solar-wind-battery EV park	MATLAB sizing tool	Multi-location China data	WOA for optimal sizing
Mbungu et al.	2022	Stochastic MPC	Hybrid renewable microgrid	Simulation benchmark	Synthetic scenario data	MPC uncertainty comparison
Patel et al.	2022	CNN imitation learning	Solar-battery EV	HIL with LFP battery	Optimal controller labels	CNN EMS with low latency
Saleh et al.	2023	Deep GNN	Solar-wind-EV microgrid	MATLAB Simscape	Simulated fault data	GNN fault detection
Ahmad et al.	2023	Moth-Flame Optimization	Solar-wind-EV with V2G	Multi-objective framework	Norwegian demo project	MFO for V2G scheduling
Zhao et al.	2023	Adaptive Dynamic Programming	Fuel cell-battery-solar HEV	Chassis dynamometer	WLTP, US06 cycles	ADP for online EMS
Ibrahim et al.	2023	Genetic Algorithm + HOMER	Solar-wind-battery microgrid	HOMER Pro software	Sub-Saharan Africa data	Rural EV charging feasibility
Nguyen et al.	2023	Attention encoder-decoder	Solar-EV campus microgrid	Python deep learning	3-year campus metering data	Joint solar-load forecasting
Sharma et al.	2023	Soft Actor-Critic	Wind-battery EV charging	Python RL environment	Real-time electricity prices	SAC for V2G control
Xu et al.	2024	Graph Attention Network	Solar-wind-EV distribution	IEEE 33-bus test network	Synthetic + meteorological	Spatial-temporal GAT
Chen et al.	2024	Similarity-Navigated GNN	Multi-source EV system	Python GNN framework	Battery + microgrid data	SN-GNN for energy prediction
Ali et al.	2024	Red Panda Optimization	Solar-wind-battery EV infra	MATLAB optimization	Benchmark EMS instances	RPOA multi-objective dispatch
Singh et al.	2024	GNN + Genetic Algorithm	Solar-EV with V2G	UK V2G pilot data	Pilot project metering	Bilevel V2G optimization

Comparative Analysis

An examination of the studies catalogued above reveals several prominent trends in the evolution of AI-based energy management systems for electric vehicles integrated with solar and wind energy sources. Perhaps the most significant overarching trend is the progressive migration from model-based and rule-based methods toward purely data-driven and hybrid AI-metaheuristic architectures, reflecting growing confidence in the capacity of machine learning to capture the complex, non-linear dynamics of renewable energy systems without requiring explicit mathematical models. This transition has been enabled by the increasing availability of high-quality operational data from deployed microgrid and EV systems, as well as by substantial advances in deep learning software frameworks and computational hardware.

Reinforcement learning methods appear prominently across the surveyed literature, with deep Q-networks, proximal policy optimization, and soft actor-critic algorithms all demonstrating competitive performance in EMS optimization tasks. A common advantage reported for RL approaches is their ability to learn adaptive control policies that generalize across variable operating conditions, a capability that rule-based and model-predictive methods struggle to achieve without extensive scenario coverage. However, RL methods consistently require large volumes of training experience, raising practical concerns about deployment in safety-critical physical systems where unsafe exploration must be prevented.

Graph neural networks represent the most rapidly growing methodological category within the recent literature, driven by recognition that energy networks possess inherently graph-structured properties that are poorly captured by conventional Euclidean deep learning architectures. The progression from basic GCNs through GATs to the SN-GNN reflects a consistent trend toward more selective and context-aware information aggregation mechanisms, with each architectural advance yielding measurable improvements in prediction accuracy for battery state estimation and energy flow forecasting tasks. The SN-GNN's similarity-navigated attention mechanism is particularly noteworthy for its capacity to dynamically reweight inter-node communications based on learned feature relevance, enabling more effective learning from heterogeneous energy graphs with varying node types and connection strengths.

In the domain of metaheuristic optimization, there is a clear trend toward more sophisticated and adaptive algorithms that address the limitations of classical PSO and GA approaches. The Red Panda Optimization Algorithm, Whale Optimization Algorithm, and Moth-Flame Optimization all demonstrate competitive or superior performance relative to established baselines, particularly in high-dimensional multi-objective scenarios. The RPOA's dual-phase exploration-exploitation structure and memory-guided movement operators appear to be particularly effective for escaping local optima in the non-convex energy dispatch problem, as evidenced by its production of more diverse and well-distributed Pareto fronts compared to competing algorithms.

Dataset usage patterns across the reviewed literature reveal a predominance of simulation-based evaluation, with real-world deployment datasets appearing in a minority of studies. This reflects the practical difficulty of collecting sufficiently large and representative operational datasets from physical EV-solar-wind systems, which are still relatively rare in deployed form. The use of standard benchmark datasets such as the NREL wind integration study and EPA driving cycles facilitates cross-study comparison but may underrepresent the conditions encountered in novel deployment contexts such as Sub-Saharan Africa or island microgrids. Hardware-in-the-loop validation, appearing in a subset of the reviewed studies, represents a methodologically rigorous intermediate step between pure simulation and real-world deployment that provides confidence in controller timing and hardware compatibility.

Discussion

The synthesis of the reviewed literature highlights that no single methodological approach currently dominates all aspects of energy management systems (EMS) for electric vehicles integrated with renewable energy sources. Instead, each technique contributes distinct strengths depending on the problem context. Rule-based and fuzzy logic systems remain useful in low-complexity or resource-constrained environments due to their interpretability and ease of implementation. However, they lack adaptability under dynamic operating conditions. Deep reinforcement learning methods provide strong performance in sequential decision-making and long-term scheduling, particularly in environments with variable renewable generation. Graph neural networks have proven highly effective for modeling spatially and structurally complex energy systems, while metaheuristic optimization techniques continue to be widely used for multi-objective dispatch problems where analytical gradients are unavailable.

A key insight from the literature is that hybrid AI frameworks consistently outperform standalone approaches by combining complementary advantages. For instance, combinations such as GWO-DNN and GNN-GA demonstrate improved robustness by integrating predictive learning with global optimization capabilities. Similarly, the integration of graph-based deep learning with evolutionary or swarm-based optimization provides a powerful mechanism for handling both representation learning and decision optimization simultaneously. The RPOA-SN-GNN framework aligns with this trend by using similarity-aware graph representations to enhance optimization efficiency. Across multiple studies, improvements in forecasting accuracy and state estimation directly translate into measurable gains in EMS efficiency, cost reduction, and renewable energy utilization when properly embedded within control systems.

Despite these advancements, a major limitation identified across the literature is the gap between simulation-based performance and real-world deployment. Many proposed models achieve strong results in controlled environments but fail to fully account for practical constraints such as sensor noise, communication delays, hardware limitations, and battery aging effects. Only a limited number of studies validate their approaches using hardware-in-the-loop or real experimental setups, and these often show performance degradation compared to simulation results. This discrepancy underscores the need for more robust validation frameworks and real-time implementation-focused research to ensure practical applicability of AI-based EMS solutions. Another critical aspect is battery degradation management, which plays a decisive role in the long-term viability of EV systems. While several studies incorporate degradation-aware optimization, the accuracy and computational efficiency of these models vary significantly. Recent graph neural network-based approaches offer promising improvements in real-time battery state estimation and health monitoring, enabling more informed energy management decisions. Additionally, vehicle-to-grid (V2G) integration introduces both opportunities and complexities by enabling bidirectional energy flow and additional revenue streams, but it also increases optimization complexity due to battery wear considerations and grid coordination requirements. Overall, the literature indicates that future EMS development must prioritize hybrid intelligent systems, real-world validation, and degradation-aware control strategies to achieve scalable and sustainable deployment.

Conclusion

This comprehensive review of artificial intelligence techniques for energy management systems (EMS) in electric vehicles integrated with solar and wind power examines evolving research spanning rule-based control, reinforcement learning, graph neural networks, and metaheuristic optimization. Findings show AI-based EMS outperform traditional deterministic methods in renewable-integrated EV systems and future solutions will rely on hybrid AI architectures combining multiple learning and optimization approaches. Among key contributions, the Red Panda Optimization Algorithm (RPOA) and Similarity-Navigated Graph Neural Network (SN-GNN) are promising. SN-GNN improves similarity-aware representation learning for energy networks enhancing forecasting and state estimation across solar wind battery and EV components. RPOA improves optimization via exploration-exploitation strategy increasing robustness in high-dimensional non-convex EMS problems. Their integration enables data-driven prediction and real-time decision-making exceeding isolated methods. The literature emphasizes key design principles including accurate short- and medium-term forecasting of renewable generation and EV demand, incorporation of battery degradation into multi-objective optimization, graph-based energy dependency modeling, and V2G integration enabling EVs as distributed resources for grid stability and economic benefits. Future work includes scalable GNNs, uncertainty-aware, federated learning, digital twins, quantum-assisted optimization, second-life batteries sustainable EMS.

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