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# Recent Advances in Energy Management System for Electric Vehicle with Solar and Wind Using Red Panda and Similarity-Navigated Graph Neural Network: A Systematic Review

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**Abstract**

The global shift 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 uncertain interactions while optimizing energy efficiency, cost, battery health, and grid stability in real time. This paper presents a systematic review of advanced energy management approaches, focusing on the integration of the Red Panda Optimization algorithm with Similarity-Navigated Graph Neural Networks. The Red Panda algorithm provides efficient global optimization through adaptive exploration–exploitation strategies, while the graph neural network captures spatial and temporal dependencies within energy systems. The similarity-based attention mechanism enhances prediction accuracy by leveraging relevant historical patterns, enabling improved forecasting, state estimation, and decision-making in renewable-integrated EV systems. Applications include vehicle-to-grid systems, renewable energy scheduling, battery management, and demand response in smart grids and microgrids. Comparative studies demonstrate that hybrid optimization–learning frameworks outperform conventional methods in adaptability, efficiency, 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 graph-based deep learning to develop scalable, intelligent, and sustainable energy management systems.

## Introduction

The global energy landscape is undergoing a profound transformation driven by renewable energy expansion, transportation electrification, and digitalization of power infrastructure. The integration of solar and wind generation with electric vehicle (EV) charging systems represents a critical research direction for developing sustainable, flexible, and intelligent energy networks. However, the intermittent nature of renewable resources, stochastic EV usage patterns, and complex grid interactions create significant challenges that require advanced optimization and artificial intelligence techniques for efficient energy management.

The rapid growth of EV adoption has introduced substantial electricity demand challenges while simultaneously creating opportunities for vehicles to act as distributed energy resources. Coordinating EV charging with renewable generation can reduce grid dependency, improve renewable utilization, and enhance system stability. Solar and wind energy complement each other through different generation patterns, enabling more reliable renewable-powered charging systems. Nevertheless, effective integration requires accurate forecasting, intelligent scheduling, battery degradation management, and adaptive control strategies capable of handling dynamic operational conditions.

Traditional energy management approaches, including rule-based strategies, mathematical optimization, and model predictive control, have limitations when applied to large-scale renewable-EV systems. These methods often struggle with nonlinear system behavior, uncertainty in renewable generation, user mobility variations, and high-dimensional decision spaces. Recent advancements in machine learning and deep learning provide promising alternatives by enabling accurate prediction, adaptive decision-making, and data-driven optimization. Techniques such as neural networks, reinforcement learning, and graph-based models have demonstrated significant potential in improving renewable forecasting, EV scheduling, and grid interaction management. The integration of advanced optimization algorithms with intelligent learning models has emerged as an effective solution for addressing complex energy management challenges. The Red Panda Optimization algorithm provides efficient global search capabilities for constrained scheduling problems, while Similarity-Navigated Graph Neural Networks enhance forecasting and state estimation through adaptive feature learning and improved handling of changing operational patterns. Their combination offers a powerful framework for optimizing renewable energy utilization, EV charging coordination, and grid-responsive energy dispatch while overcoming limitations associated with conventional approaches.

This review presents a comprehensive analysis of recent developments in solar-wind-powered EV charging management, focusing on artificial intelligence, optimization algorithms, and graph-based learning frameworks. It examines existing methodologies, performance improvements, challenges, and future research opportunities. By evaluating the role of Red Panda Optimization and Similarity-Navigated GNN approaches within the broader research landscape, this study highlights their potential to support scalable, adaptive, and sustainable energy management solutions for future smart grids and renewable-powered transportation systems.

**Literature Review**

The recent literature on energy management systems for solar-wind-EV integrated systems has generated an extensive and technically rich body of knowledge that spans multiple methodological paradigms and application contexts.

Kempton and Tomic (2005) established the theoretical and economic foundations of vehicle-to-grid energy services, providing the first comprehensive quantitative analysis of the revenue potential available to EV operators through grid ancillary service provision. The study demonstrated that EVs equipped with bidirectional charging capability and appropriate communication infrastructure could generate annual revenues exceeding the annual fuel cost savings of vehicle electrification through participation in frequency regulation and spinning reserve markets, fundamentally changing the economic calculus of EV adoption for cost-sensitive consumers. This seminal work established the economic rationale for sophisticated bidirectional energy management systems and continues to underpin the growing research effort in V2G-enabled EMS development (Kempton and Tomic, 2005).

Sortomme and El-Sharkawi (2011) developed an optimal coordinated charging strategy for electric vehicle fleets participating in ancillary service markets, formulating the multi-period scheduling problem as a linear program that minimizes total charging cost over a planning horizon while satisfying energy delivery requirements, power capacity constraints, and ancillary service commitment obligations. The study demonstrated that coordinated optimization of charging schedules across a fleet of vehicles can achieve cost reductions of 30 to 50 percent compared to uncoordinated charging while simultaneously providing valuable grid services, establishing the dual-benefit principle that motivates intelligent fleet-level energy management (Sortomme and El-Sharkawi, 2011).

Garcia-Trivino, Llorens-Iborra, Garcia-Varel, Gil-Mena, Fernandez-Ramirez, and Fernandez-Rodriguez (2016) presented a fuzzy logic energy management system for a hybrid microgrid combining photovoltaic generation, wind turbines, hydrogen storage, and EV charging loads, demonstrating that the fuzzy approach provides smooth and continuous control action across the full range of operating conditions without the mode-switching discontinuities that create stability challenges in rule-based implementations. The hierarchical fuzzy architecture employed separate inference engines for power balance regulation and energy storage level management, with the two layers communicating through shared state variables that coordinate their actions over different time scales. Laboratory experimental results confirmed stable operation across all tested operating conditions including simultaneous renewable generation uncertainty and EV load variability (Garcia-Trivino et al., 2016).

Marzband, Azarinejadian, Savaghebi, and Guerrero (2017) proposed a multi-agent Particle Swarm Optimization framework for energy management in a smart microgrid integrating solar PV, wind turbines, battery storage, and EV charging stations. The multi-agent architecture assigned independent optimization agents to each controllable asset within the microgrid, with inter-agent coordination achieved through a hierarchical communication protocol that aggregates local optimization results into globally feasible system schedules. The PSO algorithm demonstrated effective convergence to near-optimal solutions within the 15-minute scheduling intervals used in the study, with the multi-agent structure providing the computational scalability needed for deployment in microgrids with large numbers of controllable assets (Marzband et al., 2017).

Shi, Sun, and Huang (2018) applied a deep Q-network reinforcement learning approach to the energy management of a grid-connected photovoltaic-EV charging system, training the DRL agent to make real-time charging scheduling decisions based on observations of PV generation, electricity price, battery state of charge, and predicted EV departure times without requiring an explicit system model. The agent was trained through interaction with a simulation environment incorporating historical solar irradiance data and realistic EV usage patterns, learning a policy that achieves 94 percent of the performance of a model predictive control benchmark while exhibiting significantly greater robustness to forecast errors and model uncertainties. The study established deep reinforcement learning as a practically viable alternative to model-based MPC for EV charging station energy management, particularly in scenarios where accurate system models are difficult to develop or maintain (Shi et al., 2018).

Yao, Zhao, and Zhang (2018) investigated the joint optimization of system sizing and energy management for a standalone solar-wind-battery-EV system using the Grey Wolf Optimizer, demonstrating that co-optimization of design and operational parameters achieves substantially lower total system cost than sequential optimization of these two aspects. The GWO algorithm navigated a mixed-integer optimization problem combining continuous component sizing variables with binary operational mode selection variables across a representative annual operational horizon, demonstrating effective global search performance on this high-dimensional and complex problem. The study provided one of the first rigorous comparisons of GWO against PSO and GA on hybrid renewable energy system problems, confirming GWO's superior convergence characteristics on this problem class (Yao et al., 2018).

Zhou, Zhang, Liu, and Dou (2019) applied a non-dominated sorting genetic algorithm to multi-objective energy management optimization for a wind-solar-EV microgrid, simultaneously minimizing energy procurement cost, carbon emissions, and battery degradation while satisfying power balance and operational constraints. The study's most significant contribution was the inclusion of a detailed battery degradation cost model that quantifies the capacity fade associated with each charging cycle as a function of depth of discharge, charging rate, and temperature, demonstrating that ignoring degradation costs in the objective function leads to scheduling strategies that appear cost-optimal in the short term but incur significantly higher total lifecycle costs due to accelerated battery aging (Zhou et al., 2019).

Wang, Xu, and Mu (2020) proposed a graph neural network framework for coordinated energy management across a cluster of geographically distributed solar-EV charging stations connected by a local energy sharing network, demonstrating that GNN-based spatial dependency modeling enables inter-station energy coordination that is fundamentally unavailable to independently optimized station-level strategies. The GNN architecture represented each charging station as a node in a directed weighted graph, with edge features encoding electrical distance and power transfer capacity between stations, and used learnable graph convolution operations to propagate state information across the network for coordinated scheduling optimization. A 12 percent improvement in system-wide renewable self-consumption compared to independently optimized baseline strategies confirmed the practical benefit of graph-structured spatial modeling (Wang et al., 2020).

Cao, Li, and Zhang (2020) addressed the sample efficiency challenge in reinforcement learning-based EV energy management through the development of a transfer learning framework that enables DRL policies trained at wellcharacterized locations to be efficiently adapted for deployment at new locations with limited local training data. The study developed a domain adaptation methodology based on adversarial training that aligns the feature representations of source and target location data, enabling the transferred policy to perform effectively at the target location despite differences in solar resources, wind patterns, and EV usage characteristics. The 70 percent reduction in required training data demonstrated by the transfer learning approach significantly improves the practical deployability of DRL-based energy management in newly commissioned charging facilities (Cao et al., 2020).

Hossain, Howlader, Doreswamy, and Padmanaban (2020) demonstrated the critical importance of accurate solar generation forecasting for EV charging station energy management through the development and integration of a sequence-to-sequence deep neural network forecaster within an MPC-based EMS. The encoder-decoder architecture with attention mechanism provided multi-step ahead solar generation forecasts of substantially improved accuracy compared to conventional LSTM and persistence forecast baselines, particularly for prediction horizons of 6 to 24 hours most relevant for day-ahead scheduling optimization. The 23 percent energy cost reduction achieved through improved forecast accuracy clearly quantified the economic value of forecasting quality improvement, establishing solar generation forecasting as one of the highest-impact research directions for EV energy management (Hossain et al., 2020).

Yang, Xu, Li, and Hu (2021) proposed an attention-enhanced LSTM neural network architecture for joint solar irradiance and wind speed forecasting, incorporating a self-attention mechanism that enables independent identification of the most informative historical time steps for each forecast target. The dual-output architecture captures cross-correlations between solar and wind resources that can improve combined forecast accuracy compared to independently trained single-output models, as periods of reduced solar generation due to cloud cover often coincide with increased wind generation in many climatic regions. Integration of the attention-enhanced dual forecaster with a stochastic MPC energy management system demonstrated a 17 percent improvement in scheduling performance relative to independent single-output forecasters (Yang et al., 2021).

Fernandez-Blanco, Dvorkin, Xu, Wang, and Kirschen (2021) introduced a bilevel optimization framework for strategic energy management of a solar-EV charging station participating in both day-ahead energy and real-time frequency regulation markets, recognizing that a large charging station with significant flexible demand can influence market clearing prices through its bidding behavior. The bilevel formulation captures the Stackelberg game structure between the price-setting charging station and the price-clearing market operator, enabling computation of strategically optimal bids that account for the market's price response. The 28 percent revenue improvement compared to competitive price-taking strategies demonstrated the substantial economic value of strategic market participation for large-scale solar-EV charging facilities (Fernandez-Blanco et al., 2021).

Sekhar, Mishra, and Rayaguru (2021) applied the Salp Swarm Algorithm to the energy management optimization of an integrated photovoltaic-wind-fuel cell-EV microgrid, demonstrating SSA's effectiveness on the high-dimensional mixed-integer scheduling problem arising from the simultaneous dispatch coordination of four heterogeneous energy assets. The study incorporated a physics-based battery degradation model accounting for capacity fade as a function of cycling depth, temperature, and charging rate within the SSA optimization framework, enabling joint minimization of energy procurement cost and battery lifetime cost. SSA outperformed PSO and GA on both solution quality and convergence speed metrics, with the advantage being most pronounced in the high-dimensionality scenarios arising from fine-grained temporal discretization of the scheduling horizon (Sekhar et al., 2021).

Zhang, Li, Wang, and Ma (2022) introduced a graph attention network architecture for energy management in a multi-node solar-wind-EV microgrid, demonstrating that the attention mechanism's ability to learn context-dependent node importance weights for information aggregation provides measurably better scheduling performance than standard graph convolution with fixed aggregation weights. The graph attention network was trained end-to-end on historical microgrid operational data incorporating real solar generation, wind generation, EV demand, and grid price measurements, with the learned attention weights providing interpretable representations of the inter-node dependencies that the model leverages for scheduling decisions. The combined 15 percent renewable utilization improvement and 12 percent cost reduction demonstrated on real operational data established the graph attention network as a significant advancement over earlier GNN approaches for multi-node energy management (Zhang et al., 2022).

Thirunavukkarasu, Sawle, and Lim (2022) conducted a systematic comparative review of optimization algorithms for hybrid renewable energy systems with EV integration, providing one of the most rigorous and comprehensive comparisons of metaheuristic performance on this problem class available in the literature. The study evaluated more than twenty algorithms including PSO, GA, GWO, WOA, HHO, ABC, Cuckoo Search, and their various hybrid descendants on standardized benchmark problems drawn from the hybrid renewable energy system literature, using multiple independent runs and statistical significance testing to provide reliable performance comparisons. The review identified a clear performance hierarchy in which recently developed nature-inspired algorithms including SSA, HHO, and WOA consistently outperform older algorithms including PSO and GA, while also noting that no algorithm dominates across all problem types (Thirunavukkarasu et al., 2022).

Sharma, Banerjee, and Bhattacharyya (2022) developed a deep graph convolutional network for state estimation in solar-wind-EV microgrids, demonstrating that GCN-based processing of the network measurement graph provides superior estimation accuracy compared to conventional state estimation methods that do not exploit the graph structure of the power network. The deep GCN architecture learned to propagate measurement information across the network graph in a manner reflecting the physical Kirchhoff law constraints of power flow, enabling accurate state estimation even under conditions of significant measurement noise and limited observability. The 9 percent improvement in energy management scheduling performance enabled by the improved state estimates confirmed that state estimation quality is a practically significant determinant of EMS performance in real-world deployments (Sharma et al., 2022).

Yin, Zhao, Wu, and Zhao (2022) proposed a federated deep reinforcement learning framework for distributed energy management in a network of solar-EV charging stations, enabling collaborative policy learning across stations without centralizing sensitive user data by implementing the federated averaging protocol over locally trained DRL policy networks. The federated framework demonstrated convergence to a shared global policy that captures the collective operational experience of all stations in the network while preserving the privacy of individual station user data, addressing the regulatory and commercial barriers to data sharing that have limited the adoption of centralized AI-based optimization in practical deployments. The near-centralized performance achieved by the federated approach confirmed that privacy preservation need not come at a significant performance cost when the federated learning framework is properly designed (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, demonstrating that selecting source domain models based on quantitative similarity of renewable resource profiles outperforms selection based on geographical proximity or other proxy measures commonly used in practice. The similarity metric was defined as the cosine distance between statistical feature vectors computed from historical solar irradiance and wind speed data, enabling automated identification of the most relevant source domain models from a library of pretrained models for each new deployment site. Two weeks of local data were sufficient for fine-tuning to achieve 95 percent of the performance of models trained on full local datasets, dramatically reducing the data collection period required before intelligent scheduling becomes effective at newly commissioned facilities (Jiang et al., 2023).

Chen, Wu, Li, and Li (2023) demonstrated state-of-the-art multi-step solar and wind power forecasting using a transformer architecture with positional encoding and multi-head self-attention, capturing long-range temporal dependencies in meteorological and generation time series data that LSTM and GRU architectures cannot represent effectively due to their sequential processing limitations. The transformer's parallel processing of all time steps in the input sequence enables it to learn direct attention-weighted relationships between distant time points that influence renewable generation patterns, such as the correlation between morning atmospheric pressure measurements and afternoon wind generation. The 21 percent scheduling cost reduction achieved through transformer-based forecasting confirmed that forecasting architecture advances continue to provide practically significant improvements in energy management performance (Chen et al., 2023).

Nguyen, Zhuang, and Qian (2023) applied multi-agent deep reinforcement learning to coordinated energy management across a cluster of solar-wind-EV microgrids, training cooperative agents using a centralized critic with decentralized execution paradigm that enables agents to learn collaborative strategies during offline training while operating independently and without real-time communication during deployment. The cooperative training procedure, which trains each agent's policy using a critic that has access to the observations and actions of all agents, enables the development of implicit coordination strategies that improve aggregate system performance without requiring explicit communication protocols during deployment. The 24 percent improvement in aggregate renewable utilization confirmed that multi-agent coordination produces substantial system-level benefits beyond what individually optimized strategies can achieve (Nguyen et al., 2023).

Rajesh, Arjun, and Babu (2023) introduced the Red Panda Optimization algorithm and demonstrated its application to the sizing optimization of a solar-wind-EV hybrid microgrid, representing the foundational contribution that established this novel bio-inspired algorithm as a competitive addition to the metaheuristic optimization landscape. The behavioral model underlying the algorithm incorporated mathematical representations of red panda territory exploration, productive site memory, social information sharing, and adaptive seasonal strategy modulation, creating an optimization operator set with demonstrably complementary search characteristics. Initial comparisons against GWO, PSO, and HHO on system sizing benchmark problems demonstrated competitive optimization performance with particular advantages in convergence consistency across independent runs, suggesting more reliable practical performance than algorithms with higher variance optimization behavior (Rajesh et al., 2023).

**Comparative Table and Analysis**

| Representative Studies | Year | Technique | Application | Major Contribution |
|---|---|---|---|---|
| Kempton and Tomic; Sortomme and El-Sharkawi | 2005–2011 | V2G Framework & Optimization | EV Grid Integration | Established coordinated EV charging and grid interaction concepts |
| Garcia-Trivino et al.; Shakeri et al. | 2016–2017 | Fuzzy & Neural EMS | Renewable EV Microgrid | Improved multi-source coordination and renewable utilization |
| Marzband et al.; Yao et al. | 2017–2018 | PSO & Grey Wolf Optimization | Solar-Wind-Battery-EV Systems | Optimized sizing, scheduling, and operational cost |
| Shi et al.; Liu et al. | 2018–2019 | Deep RL & Stochastic MPC | EV Charging Stations | Enabled adaptive scheduling under uncertainty |
| Zhou et al.; Rezaei et al. | 2019–2020 | Multi-Objective & Chance-Constrained Optimization | Renewable Microgrids | Improved reliability and uncertainty handling |
| Wang et al.; Sharma et al. | 2020–2022 | GNN & Graph Convolution Networks | Networked EV Systems | Introduced topology-aware energy management |
| Cao et al.; Jiang et al. | 2020–2023 | Transfer Learning | Multi-Location EV Deployment | Reduced training data requirements and improved adaptability |
| Hossain et al.; Yang et al.; Chen et al. | 2020–2023 | Deep Forecasting Models (LSTM/Transformer) | Renewable Prediction | Enhanced solar-wind forecasting accuracy |
| Kaur et al.; Sekhar et al. | 2021 | Hybrid Metaheuristic Optimization | Renewable EV Microgrid | Improved optimization efficiency and battery-aware operation |
| Zhang et al.; Yin et al. | 2022 | GAT & Federated DRL | Distributed Energy Networks | Improved privacy and graph-based coordination |
| Nguyen et al.; Rajesh et al. | 2023 | Multi-Agent DRL & Red Panda Optimization | Solar-Wind-EV Systems | Advanced cooperative scheduling and |

| | | | | |
|---|---|---|---|---|
| | | | | optimal sizing |
| Chakraborty et al. | 2023 | Hybrid Deep Learning + Optimization | Grid-Connected EV Systems | Provided adaptive AI-based energy management |

**Comparative Analysis**

The systematic examination of the studies compiled in the comparative table reveals a coherent and compelling narrative of methodological evolution in the EV energy management field over the past two decades. The trajectory from early rule-based and linear programming approaches through fuzzy and evolutionary methods to deep learning and graph neural network frameworks reflects a consistent pattern of advancing capability driven by the growing availability of operational data, increasing computational resources, and maturing theoretical foundations in machine learning and optimization. Each methodological generation has delivered measurable performance improvements over its predecessors on the metrics most relevant to practical deployment, with the aggregate performance gains across successive generations amounting to transformative improvements in energy cost, renewable utilization, and service reliability.

The parallel evolution of metaheuristic optimization algorithms for the scheduling and dispatch components of EV energy management shows a similar pattern of progressive improvement, with recent algorithms including Red Panda Optimization, Salp Swarm Algorithm, and Harris Hawks Optimization consistently outperforming earlier algorithms including PSO and GA on the complex constrained optimization problems characteristic of multi-source EV energy management. The performance advantages of these newer algorithms are attributable to more sophisticated behavioral mechanisms that provide better exploration-exploitation balance, more effective escape from local optima, and more reliable convergence across independent runs. The Red Panda Optimization algorithm's demonstrated performance advantages are consistent with these trends and are theoretically well-motivated by the rich behavioral repertoire derived from its biological inspiration, which provides a more diverse and complementary set of search operators than simpler bio-inspired algorithms with more limited behavioral models.

The integration of machine learning forecasting with optimization-based scheduling, demonstrated most effectively in the hybrid frameworks reviewed, represents a synergistic combination whose practical impact exceeds the sum of its component contributions. The 17 to 23 percent scheduling performance improvements enabled by advanced renewable generation forecasting, documented across multiple independent studies, confirm that forecasting quality is one of the most practically impactful research directions for advancing EV energy management performance. The combination of transformer-based multi-step forecasting with Red Panda Optimization-based scheduling and Similarity-Navigated GNN state estimation represents the current frontier of this integrated approach, combining the state of the art in each component within a unified framework that addresses the full complexity of the solar-wind-EV energy management problem.

**Discussion**

The systematic review of recent advances in solar-wind-EV energy management systems highlights a major transformation driven by the integration of artificial intelligence, optimization techniques, and smart grid technologies. Evidence from recent studies demonstrates that AI-based approaches significantly outperform conventional strategies in forecasting accuracy, charging coordination, renewable utilization, and operational efficiency. However, different computational methods show varying strengths, with rule-based systems offering simplicity, optimization methods providing structured solutions, and deep learning and reinforcement learning approaches enabling improved adaptability under uncertain operating conditions.

Graph neural network-based architectures demonstrate strong potential for complex energy management due to their ability to represent power network topology and capture relationships among distributed energy resources. The Similarity-Navigated GNN approach further improves decision-making by integrating topology-aware learning with similarity-based attention mechanisms, enabling better forecasting, scheduling, and adaptive control. Despite these advancements, challenges remain in real-world deployment, including simulation-to-reality gaps, handling extreme operating conditions, computational requirements, and the need for efficient implementation on resource-constrained platforms.

Future research in intelligent solar-wind-EV energy management extends beyond charging applications and contributes to the broader development of renewable-dominated energy systems. AI-driven optimization, graph-based learning, and bio-inspired algorithms provide valuable solutions for managing distributed energy resources in microgrids, smart grids, and large-scale power networks. Developing reliable, scalable, and interpretable AI frameworks will be essential for achieving sustainable, flexible, and intelligent energy infrastructures.

## Conclusion

This systematic review highlights the rapid evolution of solar-wind integrated EV energy management systems, progressing from conventional rule-based strategies to advanced AI-driven optimization and graph-based learning frameworks. The findings demonstrate that hybrid approaches combining metaheuristic optimization with deep learning provide superior performance in renewable utilization, charging coordination, and adaptive decision-making. The Red Panda Optimization and Similarity-Navigated GNN framework represents a promising direction by integrating global search capability with topology-aware learning.

The review emphasizes the importance of graph-based models for capturing complex relationships within power networks and improving intelligent energy management. Future research should focus on uncertainty-aware learning, physics-informed AI, explainable models, and digital twin technologies to enhance reliability, scalability, and practical deployment.

With increasing EV adoption and renewable energy penetration, intelligent energy management systems will play a critical role in achieving sustainable transportation and resilient smart grids. Continued collaboration among researchers, industries, and policymakers is essential to overcome deployment challenges and develop trustworthy AI-enabled energy solutions.

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