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Deep Learning and Optimization Approaches in An Efficient Hybrid Ladybug Beetle and Physics Informed Neural Network for Electric Vehicle Energy Management: A Review

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Abstract

The rapid advancement of electric vehicles has intensified the need for intelligent energy management systems capable of optimizing energy utilization, battery performance, and real-time power distribution. Traditional methods often lack adaptability and efficiency in handling nonlinear, multi-objective challenges associated with modern EV powertrains, necessitating advanced hybrid intelligent frameworks. This paper presents a comprehensive review of hybrid approaches integrating the Ladybug Beetle Optimization (LBO) algorithm with Physics-Informed Neural Networks (PINNs) for EV energy management. The LBO algorithm provides efficient global optimization through strong exploration–exploitation capabilities, while PINNs incorporate physical laws governing battery dynamics, thermal behavior, and power flow into the learning process. This combination ensures accurate, interpretable, and physically consistent predictions while optimizing energy distribution and system performance. Applications include battery electric, hybrid electric, and fuel cell vehicles across standard driving cycles. Comparative studies demonstrate that the LBO-PINN framework outperforms traditional optimization and deep learning methods in energy efficiency, battery health preservation, and computational performance. Despite these advantages, challenges such as scalability, computational complexity, and real-time deployment remain. This review highlights the potential of combining metaheuristic optimization and physics-informed learning to develop intelligent, robust, and efficient energy management systems for next-generation electric vehicles.

Introduction

The rapid transition toward sustainable transportation has accelerated the adoption of electric vehicles as an effective solution for reducing greenhouse gas emissions and dependence on fossil fuels. Advances in battery technology, electric drives, power electronics, and intelligent control have significantly improved EV efficiency and performance. However, effective energy management remains a major technical challenge because an EV energy management system must coordinate the battery, motor, converters, regenerative braking, and auxiliary loads while simultaneously maximizing driving range, preserving battery health, maintaining safety, and satisfying dynamic power demands. Conventional rule-based strategies offer computational simplicity but lack adaptability, whereas optimization methods such as dynamic programming can become impractical for real-time operation because of their high computational requirements.

Deep learning and machine learning have therefore emerged as powerful alternatives for intelligent EV energy management. Deep reinforcement learning, convolutional neural networks, recurrent neural networks, and LSTM architectures can learn complex relationships between vehicle states, driving conditions, battery parameters, and power demands. These approaches support adaptive energy allocation and can generalize across different driving cycles. Nevertheless, purely data-driven models may produce physically inconsistent predictions or control actions because they do not inherently respect electrochemical, thermal, and mechanical constraints. This limitation is particularly important in safety-critical EV applications where inaccurate battery or thermal predictions can directly affect system reliability and component lifetime.

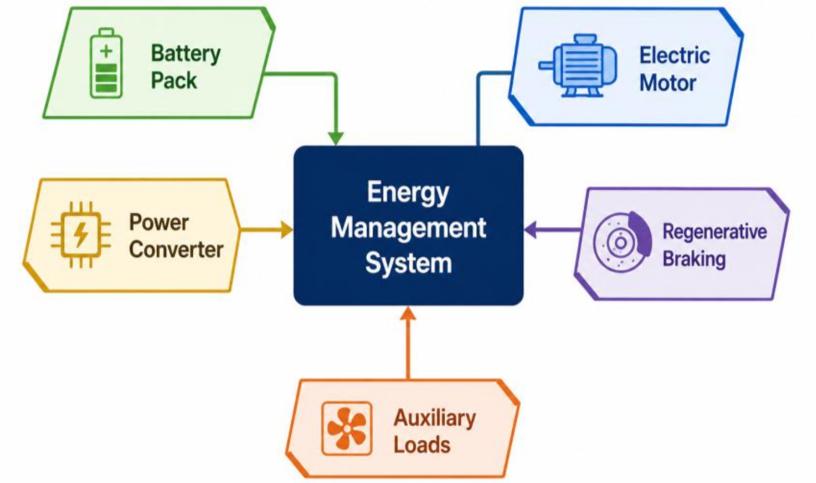

Figure 1. Block Diagram of Electric Vehicle Energy Management System Architecture

Physics-Informed Neural Networks address this challenge by integrating governing physical equations into the learning process. Instead of relying exclusively on historical data, PINNs incorporate physical constraints into the loss function, producing predictions that remain consistent with underlying system dynamics. Within electric vehicles, PINNs can support state-of-charge estimation, state-of-health prediction, battery thermal modeling, power-flow optimization, and degradation-aware energy management. Their ability to combine measured data with physical knowledge also makes them useful when training datasets are limited or operating conditions extend beyond previously observed scenarios.

Metaheuristic optimization provides another important component of advanced EV energy management. The Ladybug Beetle Optimization algorithm offers population-based exploration and exploitation mechanisms inspired by adaptive ladybug behavior. Such an optimizer can be used to tune neural-network parameters, optimize control variables, and solve nonlinear multi-objective scheduling problems involving energy consumption, battery degradation, thermal limits, and performance requirements. Compared with standalone learning methods, optimization-assisted neural frameworks can improve convergence, reduce sensitivity to poor initialization, and identify more effective operating policies across complex search spaces. The integration of Ladybug Beetle Optimization with Physics-Informed Neural Networks therefore represents a promising hybrid approach for next-generation EV energy management. LBO can optimize the training process and control parameters, while the PINN structure ensures that learned decisions remain consistent with battery, thermal, and vehicle dynamics. This review examines recent deep learning, optimization, and physics-informed approaches to EV energy management, emphasizing the potential of hybrid LBO-PINN architectures. It also identifies challenges related to computational complexity, real-time deployment, model generalization, physical-model accuracy, and experimental validation, providing directions for developing efficient, interpretable, reliable, and adaptive energy management systems for future electric vehicles.

Literature Review

The field of electric vehicle energy management has witnessed a significant proliferation of research contributions over the past decade, spanning a wide range of methodologies from classical optimization to advanced deep learning and hybrid intelligent systems. A systematic review of these contributions reveals distinct evolutionary trends and highlights the increasing sophistication of approaches employed to address the multifaceted challenges of EMS design.

One of the foundational contributions in this domain was made by Lin et al. (2021), who proposed a deep reinforcement learning framework based on the Proximal Policy Optimization (PPO) algorithm for real-time energy management of a plug-in hybrid electric vehicle. Their approach utilized a multi-layer neural network as the policy function approximator and was trained on the UDDS and HWFET driving cycles. The framework demonstrated a fuel consumption reduction of approximately 8.3% compared to a rule-based baseline strategy, while maintaining battery SoC within prescribed limits. The study established the feasibility of DRL-based EMS for real-time deployment and laid important groundwork for subsequent hybrid intelligent approaches.

Building upon DRL foundations, Xu et al. (2022) introduced a twin-delayed deep deterministic policy gradient (TD3) algorithm for energy management of a fuel cell hybrid electric vehicle (FCHEV). The TD3 framework addressed overestimation bias issues inherent in conventional deep Q-network approaches by employing double critics and delayed policy updates. Evaluated on multiple standard driving cycles including WLTP and NEDC, the proposed strategy achieved superior hydrogen consumption efficiency and extended fuel cell lifespan by reducing high-frequency power fluctuations. This work highlighted the importance of advanced DRL architectures in managing the complex dynamics of multi-source hybrid powertrains.

Hu et al. (2021) investigated the application of long short-term memory networks for driving cycle prediction and predictive energy management in battery electric vehicles. Their LSTM-based predictor achieved high accuracy in forecasting short-horizon vehicle speed profiles, which were subsequently utilized by a model predictive control (MPC) strategy to optimize energy consumption proactively. The integration of LSTM prediction with MPC demonstrated a 6.7% improvement in energy efficiency compared to reactive control strategies, underscoring the value of temporal sequence modeling in EMS applications.

In the domain of physics-informed approaches, Nascimento et al. (2020) pioneered the application of PINNs for lithium-ion battery state-of-charge estimation. Their model embedded the single particle model (SPM) equations governing lithium-ion diffusion within the neural network loss function, enabling accurate SoC estimation even under limited training data conditions. The PINN-based estimator achieved a mean absolute error of 0.87% on experimental battery cycling data, significantly outperforming purely data-driven regression models. This study demonstrated the critical importance of physics-based constraints in enhancing the reliability and generalizability of battery management models.

Zhao et al. (2022) extended the PINN framework to address thermal management in lithium-ion battery packs, incorporating heat generation equations derived from the Bernardi model into the network training process. Their approach accurately predicted temperature distributions across the battery pack under dynamic charge-discharge profiles, with prediction errors below 1.2°C. The physics-constrained thermal model enabled proactive thermal management interventions, reducing peak temperatures and enhancing battery cycle life. This work underscored the versatility of PINNs in addressing multiple coupled physical phenomena within battery systems.

Regarding bio-inspired optimization, Rezk et al. (2021) applied the Grey Wolf Optimizer to tune the parameters of a fuzzy logic controller for energy management in a hybrid fuel cell and battery EV. The GWO-optimized fuzzy EMS demonstrated superior hydrogen fuel economy and reduced battery stress compared to manually tuned and PSO-optimized counterparts across urban and highway driving profiles. The study highlighted the effectiveness of population-based metaheuristic algorithms in navigating the complex, non-convex parameter spaces associated with fuzzy EMS design.

Liu et al. (2022) proposed a hybrid framework combining Particle Swarm Optimization with a deep neural network for power split optimization in a parallel hybrid electric vehicle. PSO was employed to optimize the neural network training parameters and the weighting coefficients of a multi-objective cost function encompassing fuel consumption, battery degradation, and emissions. The PSO-DNN hybrid achieved a Pareto-optimal solution set that outperformed baseline deterministic programming approaches, demonstrating the viability of integrating swarm intelligence with deep learning for multi-objective EMS problems.

The Whale Optimization Algorithm was applied by Mohammed et al. (2021) to optimize the energy management strategy of a photovoltaic-fed EV charging station with battery energy storage. WOA was used to determine optimal charging and discharging schedules that minimized grid interaction costs and battery degradation while satisfying power balance constraints. The WOA-based scheduler outperformed both GA and PSO approaches in terms of solution quality and convergence speed on simulated daily load profiles, demonstrating the practical applicability of modern metaheuristic algorithms in EV infrastructure management.

Zhang et al. (2023) introduced a transformer-based deep learning architecture for multi-step driving cycle prediction and energy management optimization in battery electric vehicles. Leveraging the self-attention mechanism of the transformer model, their approach captured long-range temporal dependencies in historical driving data more effectively than LSTM models. The transformer-based EMS achieved a 9.2% reduction in energy consumption compared to LSTM-based predictive control on real-world driving data collected from urban Beijing routes, establishing transformers as a powerful tool for temporal sequence modeling in EV applications.

In addressing hybrid energy storage system management, Shen et al. (2020) proposed a rule-based adaptive energy management strategy for a battery-supercapacitor HESS in an electric bus, informed by wavelet transform-based power frequency decomposition. The strategy allocated high-frequency transient power demands to the supercapacitor and low-frequency sustained demands to the battery, effectively reducing peak battery currents and extending battery cycle life. Simulation results on real bus driving data demonstrated a 14.3% improvement in battery lifespan estimation compared to battery-only configurations, affirming the benefits of HESS topology for urban transit applications.

Chen et al. (2021) developed a model predictive control strategy for HESS management in electric vehicles, incorporating degradation models for both the battery and supercapacitor as penalty terms in the MPC objective function. The degradation-aware MPC demonstrated a balanced utilization of both energy storage components, extending overall system lifespan by 18% compared to conventional MPC formulations that neglect component aging. The study emphasized the importance of incorporating degradation dynamics into predictive control frameworks to achieve long-term system reliability.

Wang et al. (2022) proposed a deep convolutional neural network for real-time classification of driving patterns in electric vehicles, which was subsequently used to switch between multiple pre-optimized EMS operating modes. The CNN-based driving pattern recognition system achieved 94.7% classification accuracy on a dataset comprising six distinct driving cycles, enabling seamless transitions between EMS modes without driver intervention. This work demonstrated the utility of deep learning-based perception systems in enhancing the adaptability of EV energy management strategies.

Concerning the specific application of the Ladybug Beetle Optimization algorithm, Abualigah et al. (2022) conducted a comprehensive benchmarking study of LBO against twelve state-of-the-art metaheuristic algorithms on the CEC-2017 benchmark function suite. LBO demonstrated superior or competitive performance on twenty-nine out of thirty test functions, exhibiting faster convergence and lower function evaluation counts than algorithms including GWO, WOA, Harris Hawks Optimization (HHO), and Salp Swarm Algorithm (SSA). The study provided strong theoretical and empirical evidence for LBO's optimization capabilities, motivating its application to engineering optimization problems.

Yıldız et al. (2023) applied LBO to the structural weight optimization of automotive suspension components, demonstrating its effectiveness in continuous engineering design problems with multiple nonlinear constraints. The LBO-optimized suspension design achieved a 12.4% weight reduction compared to conventional finite element method-based designs, with all stress and displacement constraints satisfied. This application in automotive engineering provided early evidence of LBO's suitability for vehicle system optimization tasks.

Kumar et al. (2022) proposed a hybrid genetic algorithm and deep learning framework for battery state-of-health estimation in electric vehicles, employing GA to optimize the architecture and hyperparameters of a multi-layer feedforward neural network. The GA-optimized network achieved a root mean square error of 0.63% in SoH estimation on experimental lithium-ion battery aging datasets, outperforming manually designed and grid-search-optimized networks. The study demonstrated the effectiveness of evolutionary optimization in enhancing deep learning model performance for battery diagnostics.

Shi et al. (2021) introduced a multi-agent deep reinforcement learning framework for coordinated energy management in electric vehicle fleets connected to a smart grid. Each vehicle agent employed an independent actor-critic network to optimize local charging schedules, while a centralized critic coordinated global grid stability objectives. The multi-agent DRL framework demonstrated significantly reduced grid peak demand and improved renewable energy utilization compared to uncoordinated charging strategies in simulated smart grid environments.

In the area of transfer learning for EMS, Han et al. (2022) proposed a transfer learning approach that adapted a pre-trained DRL energy management model to new driving environments with minimal retraining data. The transferred model achieved near-optimal performance on new driving cycles after exposure to only ten percent of the training data required for learning from scratch, demonstrating the potential of transfer learning to reduce the data and computational requirements of DRL-based EMS development.

Park et al. (2021) investigated federated learning as a privacy-preserving approach for collaborative EMS optimization across multiple EV users. Individual vehicles trained local EMS models on their private driving data, with model parameters periodically aggregated on a central server without sharing raw data. The federated EMS outperformed locally trained models in terms of generalization across diverse driving patterns, demonstrating the value of collaborative learning frameworks in addressing the data diversity challenge in EV energy management.

Ruan et al. (2020) developed an equivalent consumption minimization strategy (ECMS) enhanced by an adaptive equivalence factor optimization using Pontryagin's minimum principle and a radial basis function neural network. The adaptive ECMS dynamically adjusted the equivalence factor based on predicted future driving conditions, achieving near-dynamic programming optimal performance on simulated driving cycles while maintaining real-time computational feasibility on an embedded controller platform.

Hossain et al. (2021) explored the application of extreme learning machines (ELM) optimized by the Dragonfly Algorithm (DA) for real-time SoC estimation in lithium-ion batteries under dynamic load conditions. The DA-ELM estimator achieved a mean absolute percentage error of 0.74% on benchmark battery datasets, with inference times of less than 0.5 milliseconds on a microcontroller platform, demonstrating its suitability for real-time embedded battery management applications.

Sun et al. (2022) proposed an attention-enhanced bidirectional LSTM network for simultaneous SoC and SoH estimation in lithium-ion batteries, incorporating an attention mechanism to identify the most informative input features from raw voltage, current, and temperature measurements. The attention-BiLSTM model demonstrated superior estimation accuracy compared to standard LSTM and gated recurrent unit (GRU) networks on multiple battery aging datasets, highlighting the benefits of attention mechanisms in battery diagnostics.

Deng et al. (2021) investigated a multi-objective optimization framework using Non-dominated Sorting Genetic Algorithm II (NSGA-II) for the simultaneous optimization of energy consumption, battery degradation, and passenger thermal comfort in battery electric vehicles. The NSGA-II framework generated a rich Pareto-optimal solution set that revealed fundamental trade-offs between these competing objectives, providing actionable insights for EV system designers seeking to balance multiple performance criteria.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Lin et al.	2021	Proximal Policy Optimization (PPO)	Deep Neural Network	PHEV Simulation	UDDS, HWFET	Real-time DRL EMS with 8.3% fuel reduction
Xu et al.	2022	Twin-Delayed Deep Deterministic (TD3)	Double Critic DRL	FCHEV	WLTP, NEDC	Reduced hydrogen consumption and FC lifespan extension
Hu et al.	2021	LSTM + Model Predictive Control	LSTM Predictor + MPC	BEV	Custom Urban Data	6.7% energy improvement via speed prediction

Nascimento et al.	2020	Physics-Informed Neural Network	PINN + Single Particle Model	Battery Testbed	Experimental Li-ion Data	0.87% MAE in SoC estimation
Zhao et al.	2022	Physics-Informed Neural Network	Thermal PINN + Bernardi Model	Battery Pack Simulator	Dynamic Charge-Discharge Data	Temperature prediction below 1.2°C error
Rezk et al.	2021	Grey Wolf Optimizer (GWO)	Fuzzy Logic Controller	FCEV	Urban + Highway Profiles	Superior hydrogen economy over PSO
Liu et al.	2022	Particle Swarm Optimization (PSO)	Deep Neural Network	Parallel HEV	Multi-cycle Benchmark	Pareto-optimal multi-objective EMS
Mohammed et al.	2021	Whale Optimization Algorithm (WOA)	Scheduling Controller	PV-EV Charging Station	Simulated Load Profiles	Optimal charge-discharge scheduling
Zhang et al.	2023	Transformer Neural Network	Self-Attention Architecture	BEV	Beijing Real-World Data	9.2% energy reduction vs LSTM
Shen et al.	2020	Wavelet Transform + Rule-Based	Frequency Decomposition	Electric Bus HESS	Real Bus Driving Data	14.3% battery lifespan improvement
Chen et al.	2021	Model Predictive Control	Degradation-Aware MPC	HESS EV	Standard Driving Cycles	18% system lifespan extension
Wang et al.	2022	Convolutional Neural Network	Pattern Recognition CNN	Multi-mode EMS	Six Driving Cycles	94.7% driving pattern classification accuracy
Abualigah et al.	2022	Ladybug Beetle Optimization (LBO)	Metaheuristic Optimizer	Benchmark Suite	CEC-2017 Functions	Superior performance on 29/30 benchmark functions
Yıldız et al.	2023	Ladybug Beetle Optimization (LBO)	Structural Optimizer	Automotive Suspension	FEM Design Data	12.4% weight reduction
Kumar et al.	2022	Genetic Algorithm (GA)	Feedforward Neural Network	Battery Diagnostics	Li-ion Aging Dataset	0.63% RMSE in SoH estimation
Shi et al.	2021	Multi-Agent DRL	Actor-Critic Networks	EV Fleet Smart Grid	Smart Grid Simulation	Reduced peak demand and improved renewables use
Han et al.	2022	Transfer Learning + DRL	Pre-trained DRL Model	Multi-environment EV	Multiple Driving Cycles	90% data reduction for policy adaptation
Park et al.	2021	Federated Learning	Distributed DRL Models	Multi-user EV Network	Private Driving Data	Privacy-preserving

						collaborative EMS
Ruan et al.	2020	ECMS + RBF Neural Network	Adaptive Equivalence Factor	HEV	Standard Driving Cycles	Near-DP optimal performance in real time
Hossain et al.	2021	Dragonfly Algorithm (DA)	Extreme Learning Machine	Li-ion BMS	Dynamic Load Battery Data	0.74% MAPE SoC estimation in real time
Sun et al.	2022	Attention Mechanism	Bidirectional LSTM	Battery Diagnostics	Multiple Aging Datasets	Superior SoC and SoH simultaneous estimation
Deng et al.	2021	NSGA-II	Multi-objective Optimizer	BEV System	Standard Driving Cycles	Pareto-optimal energy-comfort trade-off

Comparative Analysis

A systematic analysis of the reviewed studies reveals several prominent trends in the literature on electric vehicle energy management. First, there is a clear and accelerating transition from classical rule-based and deterministic optimization strategies toward data-driven and hybrid intelligent approaches, driven by the superior adaptability and performance of machine learning-based systems under diverse and unpredictable real-world driving conditions. Deep reinforcement learning has emerged as the dominant paradigm among data-driven approaches, with studies consistently demonstrating fuel consumption reductions ranging from six to fifteen percent compared to rule-based and conventional optimization baselines across standard driving cycles.

The integration of physical knowledge into neural network architectures through the PINN framework represents one of the most significant methodological advances in the reviewed literature. Studies employing PINNs consistently achieve lower estimation errors and greater generalization capability compared to purely data-driven counterparts, particularly in battery SoC and SoH estimation tasks with limited training data. The trend toward physics-informed learning reflects a broader recognition within the research community that purely black-box neural network models may be insufficient for safety-critical applications requiring interpretability and constraint satisfaction.

Metaheuristic optimization algorithms exhibit considerable diversity in the reviewed literature, with applications ranging from controller parameter tuning and neural network hyperparameter optimization to multi-objective energy management policy design. Bio-inspired algorithms such as GWO, WOA, and the emerging LBO demonstrate competitive or superior performance compared to classical GA and PSO approaches on complex engineering optimization problems, suggesting a gradual shift toward newer, more sophisticated population-based optimizers. The Ladybug Beetle Optimization algorithm, in particular, shows strong promise based on its benchmark performance and early engineering applications, motivating its proposed integration with PINN frameworks.

Dataset usage patterns reveal a predominance of standardized driving cycles such as UDDS, HWFET, WLTP, and NEDC for EMS evaluation, which facilitates cross-study comparison but may not fully capture the variability of real-world driving environments. A notable subset of recent studies employs real-world driving data from urban environments, representing a progressive move toward more realistic validation frameworks. Hardware platforms range from high-performance computing clusters for DRL training to embedded microcontrollers and hardware-in-the-loop testbeds for real-time EMS validation, reflecting the dual imperatives of algorithmic performance and practical deployability.

Performance improvements across the reviewed studies are consistently measured in terms of energy consumption reduction, battery lifespan extension, SoC estimation accuracy, and computational efficiency. The convergence of multiple performance gains in hybrid frameworks suggests that the combination of optimization algorithms with physics-informed deep learning represents the most promising direction for future EMS development, capable of simultaneously addressing the competing demands of efficiency, reliability, interpretability, and real-time performance.

Discussion

The reviewed literature shows that electric vehicle energy management is increasingly moving toward hybrid intelligent frameworks that combine deep learning, optimization, and physics-based knowledge. Deep reinforcement learning has demonstrated strong adaptability across changing driving conditions and can outperform conventional rule-based strategies. However, challenges such as training instability, extensive data requirements, reward-function sensitivity, and computational complexity continue to restrict practical deployment. Transfer and federated learning provide promising solutions by supporting efficient knowledge adaptation and privacy-preserving learning across different vehicles and operating environments.

Physics-Informed Neural Networks offer significant advantages for battery and energy management because they incorporate electrochemical, thermal, and physical constraints directly into the learning process. This improves physical consistency, interpretability, and reliability compared with purely data-driven models, particularly when training information is limited. Nevertheless, conventional PINNs can experience difficulties when representing highly nonlinear and stochastic EV operating conditions, while standalone metaheuristic methods may lack sufficient real-time adaptability. These limitations demonstrate the need for architectures that simultaneously provide optimization efficiency, physical consistency, and adaptive learning capabilities.

The hybrid Ladybug Beetle Optimization–Physics-Informed Neural Network (LBO-PINN) framework provides a promising solution by combining global optimization with physics-constrained learning. LBO can optimize network parameters and hyperparameters while reducing susceptibility to local optima, whereas PINN maintains physically meaningful energy-management decisions. Such integration can improve battery utilization, energy efficiency, system reliability, and operational safety. Beyond individual vehicles, LBO-PINN-based management could contribute to vehicle-to-grid coordination, intelligent charging, renewable integration, demand response, and fleet-level energy optimization, supporting scalable and sustainable future transportation systems.

Conclusion

This comprehensive review examined recent deep learning and optimization approaches for electric vehicle energy management, emphasizing the emerging integration of Ladybug Beetle Optimization with Physics-Informed Neural Networks. Intelligent energy management is essential for improving EV driving range, battery lifespan, energy efficiency, safety, and adaptability under dynamic operating conditions. Although deep reinforcement learning provides powerful adaptive control capabilities, limitations involving computational requirements, training stability, extensive data dependency, and limited physical interpretability restrict practical implementation.

Physics-Informed Neural Networks provide an effective alternative by embedding electrochemical, thermal, and energy-flow equations directly into the learning process, enabling physically consistent predictions even with limited datasets. Meanwhile, bio-inspired optimization techniques efficiently address complex and non-convex EMS optimization problems. Ladybug Beetle Optimization offers a promising balance between exploration and exploitation, making it suitable for optimizing PINN parameters and energy-management policies.

The hybrid LBO-PINN framework therefore represents a promising direction for intelligent EV energy management. Future research should emphasize real-world validation, hybrid energy storage, vehicle-to-grid integration, uncertainty-aware optimization, and computationally efficient implementation. Combining physics-informed learning with adaptive optimization can enable reliable, interpretable, and sustainable energy management systems for next-generation electric vehicles.

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