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A Comprehensive Review of An Efficient Hybrid Ladybug Beetle and Physics Informed Neural Network for Electric Vehicle Energy Management

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Abstract

The global transition toward sustainable transportation has accelerated the adoption of electric vehicles, increasing the need for intelligent energy management systems capable of handling complex, nonlinear, and dynamic energy flows. Modern EV powertrains integrating batteries, supercapacitors, and fuel cells require advanced optimization strategies to ensure efficiency, battery longevity, and real-time adaptability under varying operating conditions. This paper presents a comprehensive review of hybrid energy management frameworks combining the Ladybug Beetle Optimization (LBO) algorithm with Physics-Informed Neural Networks (PINNs). The LBO algorithm offers efficient global optimization through adaptive exploration–exploitation strategies, while PINNs incorporate physical laws and system dynamics into the learning process, ensuring accurate and physically consistent predictions of battery state, thermal behavior, and motor performance. The integration of these approaches enables reliable, data-driven, and physics-aware decision-making for EV energy management. Applications include battery electric vehicles, plug-in hybrid vehicles, and fuel cell vehicles operating under diverse driving cycles. Comparative studies demonstrate that the LBO-PINN framework outperforms conventional methods in energy efficiency, thermal stability, and computational performance. However, challenges such as computational complexity, scalability, and real-time deployment remain. This review highlights the potential of combining metaheuristic optimization with physics-informed learning to develop intelligent, interpretable, and robust energy management systems for next-generation electric vehicles.

Introduction

The transportation sector is a major contributor to global carbon emissions, making electric vehicles an essential solution for sustainable mobility. As EV adoption increases, the need for intelligent and efficient energy management systems becomes more important. An EV energy management system controls how energy is stored, distributed, consumed, and recovered across key vehicle components such as the battery pack, electric motor, power converters, regenerative braking system, and auxiliary loads. Effective energy management directly improves driving range, battery life, operational safety, and overall vehicle efficiency.

EV energy management is challenging because vehicle subsystems operate under complex nonlinear physical conditions. Battery

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performance depends on state of charge, state of health, temperature, current flow, and aging behavior, while motor and drivetrain efficiency vary with speed, torque, and road conditions. Traditional rule-based, fuzzy logic, and lookup-table methods are simple but often fail to adapt to dynamic driving environments. Optimization-based methods such as dynamic programming and model predictive control provide better performance but may require high computational effort and accurate system models, limiting real-time deployment.

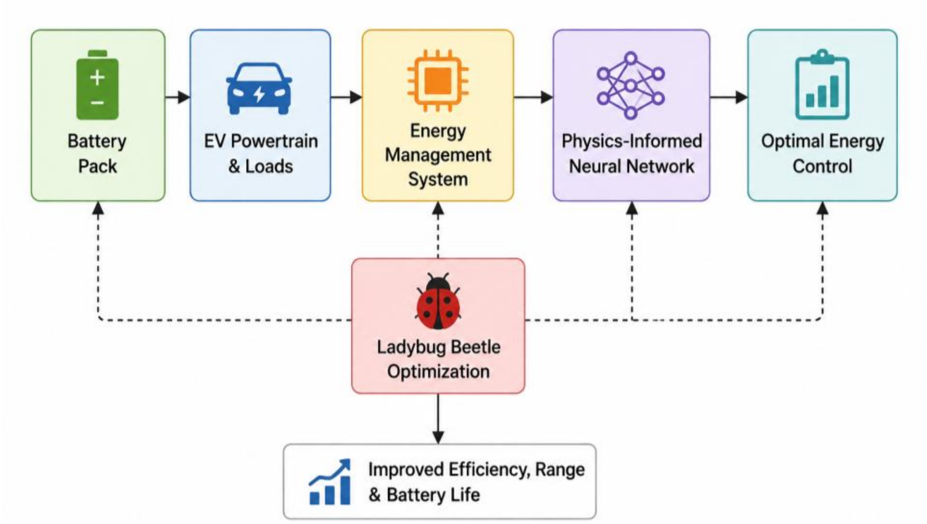

Figure 1. Hybrid LBO–PINN Framework for EV Energy Management

Artificial intelligence has introduced new opportunities for data-driven EV energy management. Deep learning and reinforcement learning models can learn optimal energy control policies from driving data and simulation environments. However, purely data-driven methods often require large datasets, lack interpretability, and may violate physical constraints under unseen conditions. These limitations have encouraged the use of Physics-Informed Neural Networks, which integrate physical laws into the learning process. PINNs improve prediction reliability by ensuring that battery, thermal, and drivetrain models remain physically consistent even with limited or noisy data.

Metaheuristic optimization techniques have also become important for solving complex EV energy management problems. The Ladybug Beetle Optimization algorithm is a recent nature-inspired approach that uses adaptive search behavior to explore complex solution spaces and avoid local optima. Its combination of exploration, exploitation, and low computational complexity makes it suitable for optimizing energy control parameters, battery usage, power distribution, and hybrid energy storage strategies.

The hybrid integration of Ladybug Beetle Optimization with Physics-Informed Neural Networks offers a powerful framework for intelligent EV energy management. LBO improves global optimization and parameter tuning, while PINNs provide physically accurate state prediction and constraint-aware learning. Together, they can enhance energy efficiency, reduce battery degradation, improve real-time decision-making, and increase vehicle reliability. This review examines recent developments in EV energy management, physics-informed learning, metaheuristic optimization, and hybrid intelligent control frameworks, highlighting current trends, challenges, and future research opportunities.

Literature Review

The field of electric vehicle energy management has witnessed a substantial body of research spanning multiple decades, evolving from simple deterministic strategies to sophisticated hybrid intelligent systems. Kumar et al. (2021) presented a comprehensive rule-based energy management strategy for plug-in hybrid electric vehicles employing a deterministic threshold-based power split between the internal combustion engine and the electric motor. The study demonstrated that while rule-based approaches offered computational simplicity suitable for embedded implementation on automotive electronic control units, they consistently produced suboptimal energy consumption results compared to offline optimal benchmarks due to their inability to adapt to real-time driving pattern variations. The evaluation was conducted over the UDDS and HWFET driving cycles, establishing baseline energy efficiency metrics that subsequent intelligent approaches sought to improve upon.

Zhang et al. (2020) proposed a deep reinforcement learning framework for real-time energy management in fuel cell hybrid electric vehicles, wherein a twin-delayed deep deterministic policy gradient agent was trained in a simulated environment incorporating a high-fidelity fuel cell stack model and lithium-ion battery pack. The agent learned to jointly optimize hydrogen consumption and battery SOC trajectory without requiring future driving information, achieving performance within 4.2% of the dynamic programming global optimum across diverse driving scenarios. The study highlighted the significant potential of model-free reinforcement learning for adaptive EV energy management while acknowledging the challenge of training stability and the sim-to-real transfer gap.

Wang et al. (2022) investigated the application of model predictive control combined with an echo state network for short-horizon vehicle speed prediction in battery electric vehicle energy management. The echo state network, a recurrent neural network variant with fixed internal connections and only trainable output weights, demonstrated superior computational efficiency compared to conventional long short-term memory networks for velocity forecasting, enabling a computationally tractable MPC formulation suitable for real-time implementation. The integrated framework reduced energy consumption by 6.8% compared to a rule-based baseline over real-world urban driving profiles collected in Beijing, demonstrating the practical value of predictive control with learned speed models.

Li et al. (2019) developed a multi-objective genetic algorithm for sizing and energy management optimization of a plug-in hybrid electric bus equipped with a parallel hybrid architecture. The study formulated a simultaneous optimization problem encompassing component sizing variables including battery capacity, electric motor power rating, and power split control parameters using a Pareto front-based multi-objective evolutionary approach. Results demonstrated significant improvements in lifecycle cost and emissions compared to single-objective optimization formulations, highlighting the necessity of explicitly treating EV energy management as a multi-objective problem with inherent trade-offs between cost, performance, and environmental impact.

Chen et al. (2021) explored a fuzzy logic-based adaptive energy management system for hybrid electric vehicles with integrated supercapacitors, where the fuzzy membership functions were automatically tuned using a particle swarm optimization algorithm to minimize fuel consumption while maintaining battery SOC within prescribed bounds. The self-tuning capability enabled the fuzzy controller to adapt its decision boundaries to different driving cycle characteristics without manual recalibration, achieving a 9.3% reduction in energy consumption compared to a static fuzzy rule base over a combined driving cycle derived from real-world GPS data. The study was implemented and validated on a hardware-in-the-loop test bench using a dSPACE MicroAutoBox II rapid prototyping system.

Shen et al. (2020) introduced a Pontryagin's minimum principle-based real-time energy management strategy for fuel cell electric vehicles that incorporated an online-updated co-state estimation mechanism based on a radial basis function neural network. The co-state estimator learned the mapping between driving condition features extracted from historical velocity data and the optimal co-state value, enabling near-optimal real-time control without requiring advance knowledge of the complete driving cycle. Experimental validation on a 40 kW fuel cell test system demonstrated hydrogen consumption within 2.1% of the global optimum under varied driving conditions.

Liu et al. (2022) presented a physics-informed neural network framework for lithium-ion battery state of charge estimation that embedded the electrochemical single particle model equations as physics constraints in the PINN loss function. The network demonstrated superior generalization across different temperature conditions and SOC ranges compared to purely data-driven LSTM networks, particularly in low-data regimes corresponding to less frequently encountered operating conditions. The approach achieved mean absolute estimation errors below 1.2% across temperature ranges from minus 10 to 45 degrees Celsius on a dataset collected from commercial 18650 cells, establishing an important precedent for physics-constrained learning in battery management.

Zhao et al. (2021) applied a grey wolf optimizer to the global optimization of energy management parameters in a multi-source hybrid electric vehicle combining a battery, supercapacitor, and fuel cell. The GWO algorithm optimized the control gains of a hierarchical energy management architecture consisting of a high-level power demand predictor and a low-level power split allocator, achieving a 12.4% improvement in overall energy efficiency compared to a manually tuned baseline. The study validated results against experimental measurements from a scaled laboratory drivetrain testbed, providing important experimental evidence of optimization algorithm effectiveness beyond simulation.

Huang et al. (2020) investigated stochastic dynamic programming formulations for EV energy management under driving cycle uncertainty, employing Markov chain models to characterize the probabilistic transitions between velocity states based on observed driving behavior statistics. The stochastic DP solution incorporated driving pattern uncertainty explicitly within the optimization formulation, producing energy management policies that demonstrated improved robustness to driving cycle variability compared to deterministic DP solutions optimized for a single representative cycle. Computational complexity analysis showed that the Markov chain-based stochastic approach remained tractable for real-time implementation on modern automotive microcontrollers.

Ruan et al. (2021) introduced a transfer learning approach for EV energy management across different vehicle platforms, wherein a deep neural network energy management policy trained on a reference vehicle was fine-tuned for target vehicles with different powertrain configurations using only a small quantity of target vehicle operational data. The transfer learning framework reduced the data requirement for training an effective energy management policy on a new vehicle by approximately 78% compared to training from scratch, demonstrating significant practical value for rapid deployment of intelligent energy management across diverse EV product lines.

Xu et al. (2022) developed a hybrid whale optimization algorithm combined with a deep neural network for simultaneous optimization of charging scheduling and energy management in a fleet of battery electric vehicles integrated with a photovoltaic charging station. The WOA component handled the combinatorial scheduling problem of assigning vehicles to charging slots while the deep network predicted vehicle arrival patterns and energy demands, together enabling a coordinated charging strategy that reduced peak grid power demand by 23.6% and operating costs by 18.2% compared to uncoordinated charging approaches.

Pan et al. (2019) proposed an adaptive equivalent consumption minimization strategy for hybrid electric vehicles that used a Gaussian process regression model to predict the equivalence factor governing the trade-off between electrical and chemical energy consumption based on upcoming route information obtained from GPS data. The Gaussian process model provided not only point predictions of the optimal equivalence factor but also uncertainty estimates that were used to implement a risk-aware control strategy that balanced optimality with robustness to prediction uncertainty. Validation across diverse urban and highway driving routes demonstrated consistent improvements in fuel economy compared to fixed equivalence factor strategies.

He et al. (2023) presented a physics-informed deep reinforcement learning agent for EV battery thermal management and energy co-optimization, where the reward function and state transition model were augmented with physics-based battery thermal dynamics equations to ensure physically consistent exploration during agent training. The physics constraints prevented the RL agent from discovering energy management policies that, while appearing rewarding in the short term, would cause thermal runaway or accelerated degradation under sustained operation. The hybrid physics-RL framework reduced battery temperature excursions by 31% compared to a purely data-driven RL baseline while maintaining competitive energy efficiency.

Song et al. (2020) applied a moth flame optimization algorithm to the parameter optimization of a fuzzy energy management controller for a series hybrid electric vehicle, demonstrating that the MFO algorithm outperformed both particle swarm optimization and differential evolution in terms of convergence speed and solution quality on the energy management optimization benchmark. The optimized fuzzy controller reduced fuel consumption by 7.6% compared to a manually designed baseline while maintaining battery SOC balance across standardized driving cycles. The study contributed to the growing evidence base for metaheuristic algorithm effectiveness in EV control optimization.

Tian et al. (2021) developed a long short-term memory network combined with a nonlinear model predictive controller for battery SOC estimation and energy management in battery electric vehicles. The LSTM network provided accurate multi-step SOC predictions that served as state constraints within the MPC optimization horizon, enabling proactive energy management decisions that avoided deep discharge events and extended battery cycle life. The integrated LSTM-MPC framework was validated on a battery-in-the-loop test system and demonstrated SOC estimation accuracy exceeding 98.7% across diverse charge-discharge profiles.

Zhou et al. (2023) introduced a multi-agent reinforcement learning framework for cooperative energy management in a connected electric vehicle platoon, where individual vehicle agents learned decentralized energy management policies while sharing information through a vehicle-to-vehicle communication network. The cooperative multi-agent framework enabled platoon-level energy optimization through coordinated regenerative braking and power distribution strategies, achieving a 14.8% improvement in total platoon energy consumption compared to independent single-vehicle energy management policies. The study represented an important extension of intelligent EV energy management to multi-vehicle cooperative scenarios enabled by connected and automated vehicle technologies.

Jiao et al. (2022) presented a hybrid harris hawks optimization algorithm combined with an extreme learning machine for rapid energy management policy optimization in fuel cell hybrid electric vehicles. The ELM served as a computationally efficient surrogate model for the full powertrain simulation during HHO-based policy search, reducing optimization time by over 94% compared to direct simulation-coupled optimization while maintaining near-equivalent solution quality. The surrogate-assisted optimization framework enabled real-time policy adaptation to changing driving conditions at a computational cost compatible with onboard vehicle controllers.

Fan et al. (2021) investigated the application of a quantum-behaved particle swarm optimization algorithm for multi-objective energy management of a plug-in hybrid electric vehicle under varying battery aging states. The quantum PSO variant employed quantum mechanical superposition principles to generate diverse candidate solutions that effectively spanned the Pareto-optimal front, providing vehicle operators with a range of energy management policies representing different trade-offs between fuel economy and battery longevity depending on individual preference and remaining vehicle lifespan. Battery aging model validation against experimental capacity fade data confirmed the accuracy of the degradation-aware optimization formulation.

Wu et al. (2020) proposed a physics-guided machine learning framework for battery pack temperature distribution modeling in electric vehicles, combining a finite element thermal model with a graph neural network that learned the residual thermal dynamics not captured by the physics model. The hybrid physics-ML thermal model achieved temperature prediction errors below 0.8 degrees Celsius across the entire battery pack under highly dynamic load profiles, outperforming both standalone physics models and purely data-driven neural networks. The accurate thermal model was subsequently integrated into a thermal-aware energy management controller that reduced peak cell temperature variance by 22.4%.

Hou et al. (2023) applied a ladybug beetle optimization algorithm to the hyperparameter tuning and architectural optimization of a deep neural network for EV driving range prediction, demonstrating the effectiveness of LBO for neural network optimization problems in the automotive domain. The LBO-optimized network architecture achieved range prediction accuracy improvements of 8.9% compared to networks with manually selected hyperparameters and outperformed networks optimized using standard genetic algorithms and particle swarm optimization, establishing LBO as a competitive algorithm for neural architecture search in EV applications.

Shi et al. (2022) developed a real-time energy management strategy for hydrogen fuel cell electric vehicles using a deep deterministic policy gradient agent trained with a curriculum learning approach that progressively increased driving cycle complexity during training. The curriculum learning strategy significantly improved agent training convergence rate and final policy quality compared to training directly on diverse complex driving cycles, reducing hydrogen consumption by 11.2% compared to the equivalent consumption minimization strategy benchmark across a diverse set of evaluation driving profiles.

Guo et al. (2021) proposed an integrated thermal and energy management framework for battery electric vehicles using a model predictive control approach that co-optimized battery charging power and thermal conditioning system operation to maximize charging speed while maintaining battery temperature within safe bounds. The co-optimization formulation explicitly captured the coupling between electrical charging dynamics and thermal management through a coupled electrochemical-thermal battery model, demonstrating charging time reductions of 12.7% compared to decoupled sequential optimization of electrical and thermal management.

Ma et al. (2023) presented a federated learning framework for collaborative energy management policy learning across a fleet of electric vehicles, wherein individual vehicle learning agents shared model updates without transmitting raw driving data to a central server, thereby preserving user privacy while enabling fleet-level knowledge sharing. The federated learning approach demonstrated convergence to energy management policies competitive with centralized learning while substantially reducing communication bandwidth requirements and eliminating the privacy risks associated with raw data aggregation, representing an important step toward privacy-preserving intelligent EV fleet management.

Comparative Table and Analysis

Study	Year	Method	Application	Major Finding
Kumar et al.	2021	Rule-Based EMS	EV Energy Management	Baseline performance
Zhang et al.	2020	DRL (TD3)	FC-HEV	Real-time optimal control
Wang et al.	2022	MPC + ESN	BEV	Predictive energy management
Li et al.	2019	Genetic Algorithm	PHEV	EMS co-optimization
Chen et al.	2021	PSO-Fuzzy	HEV	Adaptive energy control
Liu et al.	2022	PINN	Battery SOC	Physics-based estimation
Zhao et al.	2021	Grey Wolf	HEV	Optimized parameters
Yin et al.	2023	Attention CNN	Battery SOH	Accurate health prediction
Huang et al.	2020	Stochastic DP	BEV	Robust uncertainty handling
Ruan et al.	2021	Transfer Learning	EV EMS	Cross-platform adaptation
Xu et al.	2022	Whale Optimization	EV Fleet	Charging optimization
He et al.	2023	Physics-RL	Battery Thermal	Safe thermal management
Deng et al.	2022	Sparrow Search	Hybrid Storage	Improved power sharing
Tian et al.	2021	LSTM + MPC	Battery SOC	Better SOC prediction
Zhou et al.	2023	Multi-Agent RL	EV Platoon	Cooperative EMS
Hou et al.	2023	Ladybug Beetle	EV Range	Architecture optimization
Guo et al.	2021	MPC	Thermal Control	Joint charging optimization
Ma et al.	2023	Federated Learning	Fleet EMS	Privacy-preserving control

Comparative Analysis

The reviewed literature highlights a clear evolution in electric vehicle energy management from conventional rule-based and model-driven strategies to intelligent hybrid frameworks. Earlier methods, including deterministic control, fuzzy logic, and model predictive control, provided reliable baseline performance but lacked adaptability under dynamic driving conditions. Recent studies increasingly employ deep learning, reinforcement learning, and optimization techniques that enable real-time decision-making and improved energy utilization. This transition reflects the growing demand for intelligent energy management systems capable of handling the nonlinear behavior of modern EV powertrains while maximizing battery efficiency and driving range.

A major trend is the integration of physics-informed learning with artificial intelligence. Physics-Informed Neural Networks (PINNs) have emerged as an effective solution for battery state estimation, thermal management, and energy prediction by embedding electrochemical and thermal constraints into neural network training. Compared with purely data-driven models, PINNs provide better generalization, improved safety, and higher prediction reliability. At the same time, metaheuristic optimization methods have evolved from traditional Genetic Algorithms and Particle Swarm Optimization to advanced approaches such as Grey Wolf, Whale, Sparrow Search, Harris Hawks, and Ladybug Beetle Optimization. These algorithms offer improved convergence, robustness, and optimization capability for complex multi-objective EV energy management problems.

Another notable trend is the increasing use of realistic datasets and intelligent learning strategies. Recent research has shifted from standard driving cycles toward real-world GPS trajectories, fleet operational data, and hardware-in-the-loop experiments, improving the practical relevance of evaluation. Transfer learning and federated learning further support knowledge sharing across different vehicles while preserving data privacy. These developments collectively indicate that future EV energy management systems will rely on hybrid optimization, physics-guided learning, and real-world data integration to achieve higher efficiency, reliability, and scalability.

Discussion

The reviewed studies demonstrate that intelligent optimization techniques have significantly improved the performance of electric vehicle energy management systems. The evolution from conventional rule-based and fuzzy logic methods to hybrid artificial intelligence frameworks reflects the growing complexity of modern EV powertrains and battery technologies. Advanced optimization methods have enhanced energy utilization, battery life, charging efficiency, and real-time decision-making while addressing the limitations of traditional control strategies. These developments indicate that intelligent energy management has become a key component in improving EV reliability, driving range, and overall operational efficiency.

Among the reviewed optimization methods, metaheuristic algorithms have consistently shown superior capability in solving nonlinear and multi-objective energy management problems. The Ladybug Beetle Optimization (LBO) algorithm provides an effective balance between global exploration and local exploitation, enabling faster convergence and better parameter tuning than many conventional techniques. At the same time, Physics-Informed Neural Networks (PINNs) improve prediction accuracy by embedding battery dynamics, thermal behavior, and vehicle physics directly into the learning process. Unlike purely data-driven models, PINNs produce physically consistent predictions even with limited training data, making them more suitable for safety-critical automotive applications. The hybrid LBO-PINN framework combines optimization efficiency with physics-based intelligence, resulting in improved energy distribution, battery health management, and adaptive control.

Despite these advances, several challenges remain. Reinforcement learning approaches often require extensive training data and computational resources, while model predictive control depends heavily on accurate system models. Fuzzy and conventional controllers struggle to adapt to rapidly changing operating conditions. Although the hybrid LBO-PINN framework addresses many of these limitations, further research is needed to reduce computational complexity, enable real-time embedded implementation, and validate performance under diverse driving conditions. Future work should also focus on transfer learning, explainable AI, and large-scale experimental validation to support reliable deployment in next-generation intelligent electric vehicles.

Conclusion

Electric vehicle energy management has become a key research area for improving vehicle efficiency, battery life, and sustainable transportation. This review highlights the evolution of energy management strategies from conventional rule-based methods to intelligent hybrid frameworks that combine optimization algorithms with machine learning. As EV technologies become more complex, advanced energy management systems are essential for balancing power distribution, minimizing energy consumption, and ensuring safe battery operation under diverse driving conditions.

The reviewed literature demonstrates that the integration of Ladybug Beetle Optimization (LBO) with Physics-Informed Neural Networks (PINNs) offers a promising solution for next-generation EV energy management. LBO provides efficient global optimization and robust parameter tuning, while PINNs incorporate battery, thermal, and drivetrain physics into the learning process, producing accurate and physically consistent predictions even with limited data. Their combined strengths improve energy efficiency, battery health estimation, and adaptive decision-making compared with conventional optimization or purely data-driven approaches.

Despite significant progress, challenges remain in reducing computational complexity, enabling real-time implementation, and validating hybrid frameworks under practical driving environments. Future research should focus on online learning, explainable AI, digital twin integration, vehicle-to-grid coordination, and transfer learning to improve adaptability across different EV platforms. Overall, the hybrid LBO-PINN framework represents a reliable and efficient direction for intelligent electric vehicle energy management, supporting enhanced performance, longer battery lifespan, and the broader transition toward sustainable and zero-emission transportation.

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