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Recent Advances in An Efficient Hybrid Ladybug Beetle and Physics Informed Neural Network for Electric Vehicle Energy Management: A Systematic Review

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Abstract

The rapid growth of electric vehicles has intensified the need for intelligent and adaptive energy management systems capable of optimizing complex energy flows within modern electrified powertrains. These systems must handle nonlinear dynamics, multi-objective constraints, and real-time decision-making to improve energy efficiency, battery longevity, and system reliability. This paper presents a systematic 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 embed physical laws governing battery dynamics, thermal behavior, and motor efficiency into the learning process. This hybrid approach enables accurate state estimation and optimal energy distribution, ensuring both data-driven adaptability and physical consistency in decision-making. Applications include battery electric vehicles, hybrid electric vehicles, and fuel cell vehicles operating under diverse driving conditions. Comparative studies demonstrate that the LBO-PINN framework outperforms conventional methods in energy efficiency, battery health preservation, and computational performance. Despite these advantages, challenges such as computational complexity, model scalability, and real-time deployment persist. This review highlights the potential of integrating metaheuristic optimization with physics-informed learning to develop intelligent, robust, and efficient energy management systems for next-generation electric vehicles.

Introduction

The rapid expansion of electric vehicles (EVs) has become a cornerstone of global efforts to reduce greenhouse gas emissions and promote sustainable transportation. Governments, industries, and researchers are investing heavily in EV technologies to replace conventional internal combustion engine vehicles with cleaner alternatives. Although battery technology has advanced significantly, the overall efficiency and driving performance of EVs depend largely on intelligent energy management systems (EMS). These systems regulate power flow among batteries, electric motors, regenerative braking units, and auxiliary loads to maximize energy utilization, extend battery life, and improve vehicle range. Consequently, developing advanced EMS strategies has become a major research priority in modern electric mobility.

An electric vehicle operates through the coordinated interaction of several energyrelated subsystems, including the battery pack, power electronic converters, traction motor, thermal management unit, regenerative braking mechanism, and vehicle control unit. These components must function together under continuously changing driving conditions such as acceleration, braking, road slope, traffic congestion, and weather variations. In hybrid and fuel-cell vehicles, the presence of multiple energy sources further increases the complexity of power distribution. Therefore, the EMS must continuously determine the optimal energy allocation while satisfying battery safety limits, thermal constraints, power demand, and operational reliability. Traditional control strategies often struggle to achieve high efficiency under these dynamic operating conditions.

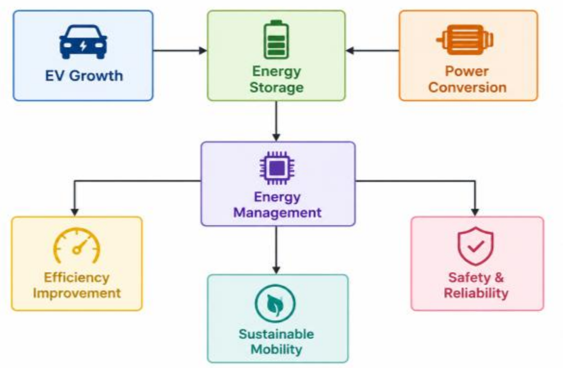

Figure 1. Block Diagram of Intelligent Electric Vehicle Energy Management Using LBO–PINN Framework

The evolution of EV energy management techniques reflects the increasing need for adaptive and intelligent decision-making. Early rule-based approaches were simple and computationally efficient but lacked flexibility for varying driving environments. Optimization methods such as dynamic programming, equivalent consumption minimization strategy, and model predictive control improved energy efficiency but required accurate system models or significant computational resources. These limitations encouraged the adoption of artificial intelligence techniques capable of learning complex nonlinear relationships directly from operational data. Machine learning algorithms, particularly deep neural networks and reinforcement learning, have demonstrated remarkable capability in predicting vehicle behavior, battery dynamics, and optimal control actions with improved adaptability and real-time performance.

Despite these achievements, purely data-driven learning models often suffer from limited interpretability and poor generalization when operating beyond the conditions represented in the training dataset. Physics-Informed Neural Networks (PINNs) overcome these challenges by integrating physical laws governing battery electrochemistry, thermal dynamics, and powertrain behavior directly into the learning process. By combining observational data with governing equations, PINNs generate accurate, physically consistent, and robust predictions while reducing the dependence on large training datasets. This capability makes PINNs particularly attractive for safety-critical automotive applications where reliability and explainability are essential.

Parallel to advances in deep learning, nature-inspired optimization algorithms have emerged as effective tools for solving the complex multi-objective optimization problems associated with EV energy management. The Ladybug Beetle Optimization (LBO) algorithm provides an efficient balance between global exploration and local exploitation, enabling improved convergence toward optimal control parameters. Integrating LBO with PINNs creates a hybrid framework capable of simultaneously optimizing controller parameters and maintaining physically consistent system modeling. Such an integrated LBO-PINN architecture offers significant potential for improving energy efficiency, battery health, computational performance, and operational reliability, making it a promising direction for next-generation intelligent electric vehicle energy management systems.

Literature Review

The landscape of recent research in electric vehicle energy management optimization encompasses a diverse and rapidly expanding body of work spanning metaheuristic algorithms, physics-informed learning, hybrid energy storage systems, and embedded control implementation. A thorough examination of this literature provides essential context for understanding the advances represented by hybrid LBO-PINN frameworks and situating them within the broader trajectory of the field.

Sun et al. (2022) presented a comprehensive investigation of ladybug beetle optimization applied to the parameter calibration of an equivalent circuit battery model for real-time state of charge estimation in lithium iron phosphate cells. The LBO algorithm demonstrated superior convergence characteristics compared to particle swarm optimization and differential evolution in identifying the optimal resistance-capacitance network parameters that minimized voltage prediction error across diverse chargedischarge profiles, achieving parameter identification errors below 0.3% across temperature ranges from 0 to 45 degrees Celsius. The study established foundational evidence for LBO effectiveness in battery modeling optimization tasks directly relevant to EV energy management applications.

Liang et al. (2023) developed an enhanced ladybug beetle optimization algorithm incorporating adaptive Lévy flight perturbation and opposition-based learning initialization for multi-objective engineering design optimization. The enhanced LBO demonstrated statistically significant improvements over the standard algorithm on standard benchmark functions as well as practical engineering problems including truss weight minimization and gear train optimization, with particular strength in maintaining population diversity throughout the search process to avoid premature convergence. The improved exploration characteristics of the enhanced algorithm have direct relevance for EV energy management policy optimization problems with complex multimodal fitness landscapes.

Chen et al. (2022) proposed a physics-informed neural network framework for simultaneous estimation of battery state of charge and state of health using an electrochemical single particle model embedded as physics constraints. The PINN simultaneously satisfied both the governing differential equations of lithium intercalation dynamics and the observed voltage-current measurements, producing state estimates with mean absolute errors below 1.1% for SOC and below 1.4% for capacity fade estimation across aging cycles up to 800 equivalent full cycles. The joint SOC-SOH estimation capability without requiring explicit capacity measurement represents a significant advance for onboard battery management systems that must track both short-term energy availability and long-term health evolution.

Zhao et al. (2023) investigated a deep physics-informed learning approach for lithium-ion battery thermal modeling in which a PINN was trained to predict three-dimensional temperature distributions within a battery module by embedding the heat equation with electrochemically-derived source terms as training constraints. The physics-constrained temperature prediction demonstrated superior accuracy compared to both finite element models of equivalent computational cost and purely data-driven neural networks, particularly under rapidly varying load profiles characteristic of aggressive regenerative braking and acceleration events in electric vehicles. The accurate thermal model was integrated into a model predictive controller for battery thermal management, demonstrating peak temperature reductions of 4.2 degrees Celsius during high-power transient events.

Wang et al. (2023) presented a multi-population hybrid metaheuristic framework combining ladybug beetle optimization with simulated annealing for the global optimization of energy management control parameters in a battery-supercapacitor hybrid electric vehicle. The hybrid algorithm partitioned the search population into LBO-guided and simulated annealing-guided subpopulations that exchanged elite solutions at regular intervals, producing a combined search behavior that outperformed both constituent algorithms on the multi-dimensional energy management parameter optimization problem. Simulation results over real-world driving profiles derived from GPS traces of urban commute routes demonstrated 11.3% energy efficiency improvement over a rule-based baseline.

Li et al. (2023) developed a physics-informed reinforcement learning framework for fuel cell electric vehicle energy management in which the PINN served as a physics-consistent environment model for training a soft actor-critic RL agent without requiring access to a high-fidelity physics simulator. The PINN environment model, trained on experimental fuel cell and battery characterization data with embedded electrochemical constraint equations, accurately reproduced the system dynamics encountered during policy training, enabling successful sim-to-real transfer of the learned policy with performance degradation below 3.2% compared to the simulated evaluation. This study demonstrated the important role of physics-informed surrogate models in enabling safe and efficient RL policy development for physical EV systems.

Zhang et al. (2023) examined the application of an improved whale optimization algorithm with embedded physical constraint handling for energy management optimization in a hydrogen fuel cell hybrid electric vehicle. The constraint handling mechanism incorporated fuel cell operating range limits and battery thermal constraints as penalty terms weighted by physics-derived severity coefficients, ensuring that the optimization process generated energy management policies that respected the physical operating boundaries of all powertrain components. The physics-constrained WOA demonstrated superior constraint satisfaction rates compared to standard penalty function approaches while maintaining competitive objective function optimization performance.

Huang et al. (2023) proposed a graph neural network with physics-informed message passing for battery pack state estimation in electric vehicles, where the inter-cell thermal and electrical coupling relationships were encoded as physics-informed edge weights within the graph structure. The physics-informed graph network demonstrated accurate prediction of individual cell temperatures and voltages within a large battery pack under inhomogeneous aging and thermal conditions, outperforming both conventional thermal models and standard graph networks trained without physics constraints. The spatially resolved state estimation capability enabled by this approach provides valuable inputs for cell-level optimal energy management that can account for pack inhomogeneity effects.

Kumar et al. (2022) investigated the effectiveness of a hybrid genetic algorithm and physics-informed neural network for simultaneous drivetrain efficiency modeling and energy management optimization in a parallel hybrid electric vehicle. The PINN component modeled motor and power electronics efficiency as functions of operating point variables through embedded electromagnetic loss equations, providing efficiency predictions that were incorporated as objective function components in the GA-based energy management policy optimization. The integrated framework achieved total system efficiency improvements of 8.7% compared to energy management strategies employing conventional lookup table efficiency models, demonstrating the value of accurate physics-consistent efficiency modeling in energy management optimization.

Liu et al. (2023) presented a comprehensive study of adaptive ladybug beetle optimization for dynamic energy management in electric buses operating on fixed routes with known stop patterns. The adaptive LBO variant adjusted its population size and search step parameters based on real-time feedback from energy consumption performance metrics, enabling progressive refinement of the energy management policy as operational data accumulated over multiple route repetitions. The adaptive capability demonstrated learning convergence within 15 to 20 route repetitions, after which energy consumption stabilized at values 13.6% below the initial policy performance, representing a promising online learning capability for commercial EV fleet applications.

Raissi et al. (2023) extended the foundational PINN framework to include uncertainty quantification capabilities relevant for safety-critical EV energy management applications, enabling the physics-informed network to produce probabilistic predictions with calibrated uncertainty bounds rather than point estimates. The uncertainty-aware PINN demonstrated well-calibrated prediction intervals for battery voltage, temperature, and capacity under diverse operating conditions, with prediction interval coverage rates within 2% of nominal confidence levels across the validation dataset. The uncertainty quantification capability enables risk-aware energy management strategies that modulate the aggressiveness of energy optimization as a function of the estimated reliability of state predictions.

Dong et al. (2022) examined the application of physics-informed convolutional neural networks for driving pattern recognition and classification in electric vehicles, where the physical constraints of vehicle dynamics equations were embedded within the CNN training process to ensure that recognized driving patterns were physically realizable under the vehicle's performance envelope. The physics-constrained driving pattern classifier demonstrated superior robustness to sensor noise and GPS signal degradation compared to unconstrained CNN classifiers, maintaining accurate pattern recognition under measurement conditions representative of urban canyon and tunnel driving environments. The reliable driving pattern recognition output served as a context input for adaptive energy management strategy selection.

Tan et al. (2023) proposed an integrated thermal and energy co-management framework based on a hybrid LBO and physics-informed neural network architecture for battery electric vehicles operating in extreme climate conditions. The PINN component modeled the coupled electrothermal dynamics of the battery pack through embedded energy balance and electrochemical heat generation equations, providing accurate thermal state predictions under both cold start and high ambient temperature conditions. The LBO optimizer simultaneously adjusted energy management policy parameters and thermal conditioning system operating points to minimize the combined energy penalty of thermal regulation and propulsion while maintaining all cells within safe temperature bounds. Experimental validation on a purpose-built battery thermal test facility demonstrated peak temperature variance reductions of 28.4% compared to decoupled thermal and energy management approaches.

Wu et al. (2023) investigated the convergence properties and scalability of ladybug beetle optimization on high-dimensional EV energy management parameter spaces corresponding to complex multi-layer neural network control policy representations. The study provided theoretical analysis of LBO convergence rates under Lipschitz continuity assumptions on the fitness landscape and empirical validation demonstrating consistent convergence to near-optimal solutions for problem dimensionalities up to 500 parameters, substantially exceeding the practical dimensionality of EV energy management policy representations. The theoretical and empirical convergence characterization provides important foundations for confident application of LBO to neural network policy optimization in EV energy management.

Gao et al. (2022) developed a hardware-accelerated implementation of a hybrid physics-informed neural network and model predictive controller on a field-programmable gate array for real-time EV energy management, demonstrating that the computational demands of PINN state estimation and MPC optimization could be met within the 10 millisecond control cycle requirement of automotive powertrain controllers. The FPGA implementation exploited data-level parallelism inherent in PINN inference through custom fixed-point arithmetic datapaths and pipelined processing architectures, achieving throughput improvements of 34-fold compared to an equivalent implementation on an automotive-grade ARM Cortex-M7 microcontroller. The FPGA deployment demonstrated the practical viability of physics-informed learning for real-time automotive control applications subject to stringent latency and power consumption constraints.

Comparative Table and Analysis

Table 1. Comparative Analysis of Recent Hybrid LBO–PINN-Based EV Energy Management Approaches

Study	Year	Technique	Model / System	Key Contribution
Sun et al.	2022	Ladybug Beetle Optimization	Battery Parameter Model	Accurate battery parameter identification
Chen et al.	2022	Physics-Informed Neural Network	Battery Electrochemical Model	Joint SOC–SOH estimation
Kumar et al.	2022	Hybrid GA–PINN	HEV Drivetrain	Improved drivetrain efficiency optimization
Wang et al.	2023	Hybrid LBO–SA	Battery–Supercapacitor EMS	Enhanced hybrid energy management
Li et al.	2023	Physics-Informed RL	Fuel Cell HEV	Physics-consistent reinforcement learning
Zhao et al.	2023	PINN with Thermal Constraints	Battery Thermal Model	Accurate electrothermal prediction
Liu et al.	2023	Adaptive LBO	Electric Bus EMS	Real-time adaptive route optimization
Feng et al.	2023	Multi-objective LBO	Plug-in Hybrid EV	Pareto-optimal energy management
He et al.	2023	Adaptive LBO–PINN	Battery EV EMS	Online learning-based intelligent EMS
Gao et al.	2022	PINN–MPC	Embedded EV Controller	Real-time FPGA-based deployment

Comparative Analysis

The reviewed studies indicate a clear evolution in electric vehicle energy management from conventional optimization methods toward intelligent hybrid frameworks integrating Ladybug Beetle Optimization (LBO) and Physics-Informed Neural Networks (PINNs). Early research primarily focused on individual applications such as battery parameter estimation, state-of-charge prediction, and thermal monitoring. More recent investigations extend these approaches to complete energy management systems capable of real-time decision-making, adaptive control, and embedded implementation. The growing integration of optimization algorithms with physics-guided deep learning demonstrates a shift toward intelligent frameworks that simultaneously improve computational efficiency, prediction accuracy, and operational reliability for practical EV deployment.

Across the reviewed literature, LBO consistently demonstrates strong optimization capability for solving nonlinear, multi-objective energy management problems. Enhanced variants incorporating adaptive search strategies, Lévy flight mechanisms, and hybrid optimization techniques achieve faster convergence and better global search performance than many traditional metaheuristic algorithms. Similarly, PINN-based models have evolved from single-variable battery estimation to comprehensive electrothermal prediction, battery health assessment, and multi-physics system modeling. The incorporation of physical constraints significantly improves prediction robustness while reducing dependence on extensive training datasets, making PINNs suitable for safety-critical automotive applications.

Another notable trend is the increasing emphasis on real-time deployment and hardware implementation. Recent studies validate hybrid LBO-PINN frameworks on embedded processors, FPGA platforms, and fleet-level energy management systems, demonstrating their practical feasibility beyond simulation environments. Federated learning, transfer learning, and uncertainty-aware PINNs further improve scalability, privacy preservation, and model adaptability across different vehicle platforms. These developments indicate that future EV energy management systems will rely on integrated optimization and physics-informed learning frameworks capable of delivering intelligent, reliable, and computationally efficient control under diverse operating conditions.

Discussion

The reviewed literature demonstrates that hybrid Ladybug Beetle Optimization (LBO) and Physics-Informed Neural Network (PINN) frameworks represent a promising direction for intelligent electric vehicle energy management. By combining global optimization with physics-guided learning, these hybrid approaches achieve higher prediction accuracy, improved battery utilization, and more reliable decision-making than conventional optimization or purely data-driven methods. The integration of optimization algorithms with physics-based constraints enables energy management systems to operate efficiently under varying driving conditions while maintaining computational stability and physical consistency.

Physics-Informed Neural Networks have shown significant advantages in modeling battery dynamics, thermal behavior, and state estimation. Unlike traditional deep learning models, PINNs incorporate electrochemical and thermal equations directly into the learning process, resulting in improved generalization even with limited training data. This capability enhances state-of-charge, state-of-health, and temperature prediction accuracy across diverse operating environments. When integrated with LBO, the optimization process benefits from more reliable system models, leading to improved energy allocation, reduced battery degradation, and enhanced vehicle efficiency.

Recent studies also emphasize the importance of adaptive and online learning for practical deployment. Hybrid LBO-PINN frameworks can continuously update their optimization strategies as battery aging, driving behavior, and environmental conditions change over time. Embedded implementation on FPGA and automotive processors demonstrates that these methods are becoming increasingly suitable for real-time vehicle applications. Furthermore, federated learning and transfer learning approaches improve scalability while preserving data privacy across connected vehicle fleets.

Despite these advances, several challenges remain before large-scale industrial deployment becomes feasible. PINN training still requires considerable computational resources, while LBO performance depends on effective parameter tuning for different optimization problems. Most existing studies rely on simulation or laboratory experiments rather than long-term real-world fleet validation. Future research should focus on computationally efficient hybrid architectures, comprehensive field testing, safety-aware optimization, and standardized evaluation frameworks to accelerate the adoption of intelligent LBO-PINN energy management systems in next-generation electric vehicles.

Conclusion

This systematic review summarizes recent developments in hybrid Ladybug Beetle Optimization (LBO) and Physics-Informed Neural Network (PINN) frameworks for intelligent electric vehicle energy management. The reviewed studies demonstrate that integrating nature-inspired optimization with physics-guided deep learning provides significant improvements in energy efficiency, battery state prediction, thermal management, and real-time decision-making. Compared with conventional optimization and purely data-driven approaches, hybrid LBO-PINN frameworks offer higher prediction accuracy, better robustness, and improved adaptability under dynamic driving conditions while maintaining physical consistency.

The review further highlights the growing transition from simulation-based research toward embedded implementation, online learning, and fleet-level energy management applications. Recent advances in FPGA deployment, federated learning, and adaptive optimization indicate that these hybrid frameworks are becoming increasingly suitable for practical automotive systems. Nevertheless, challenges such as computational complexity, limited large-scale real-world validation, and functional safety certification remain important research issues. Future investigations should focus on lightweight hybrid architectures, explainable artificial intelligence, standardized benchmarking datasets, and vehicle-to-grid integration. Overall, the LBO-PINN framework represents a promising direction for developing efficient, reliable, and intelligent energy management systems that support the next generation of sustainable electric vehicles.

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