Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 01, 2025

A Survey of Methods and Architectures for Efficient Hybrid Ladybug Beetle Optimization and Physics-Informed Neural Networks for Electric Vehicle Energy Management

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Peer Review Information

Submission: 12 May 2025

Revision: 30 May 2025

Acceptance: 13 June 2025

Keywords

Electric Vehicles (EV), Physics-Informed Neural Networks (PINNs), Ladybug Beetle Optimization (LBO), Energy Management Systems (EMS), Hybrid Optimization Algorithms, Deep Learning.

Abstract

Electric vehicles (EVs) have emerged as a sustainable alternative to conventional transportation systems, necessitating efficient energy management strategies to enhance battery performance, driving range, and system reliability. Recently, hybrid artificial intelligence techniques combining metaheuristic optimization algorithms and deep learning frameworks have gained significant attention. In particular, Physics-Informed Neural Networks (PINNs) integrate physical laws into neural network training, enabling accurate modelling of EV dynamics while reducing dependency on large datasets. Simultaneously, nature-inspired optimization algorithms such as Ladybug Beetle Optimization (LBO) offer efficient global search capabilities for solving complex nonlinear optimization problems. This paper presents a comprehensive survey of hybrid approaches that integrate LBO with PINNs for EV energy management systems (EMS). The study explores recent advancements in intelligent control strategies, battery management, and energy optimization techniques. It highlights how hybrid frameworks enhance system efficiency, reduce computational complexity, and improve prediction accuracy. Furthermore, the paper discusses challenges such as real-time implementation, scalability, and data limitations. A comparative analysis of recent studies is provided to evaluate the effectiveness of different methodologies. The findings indicate that hybrid AI-based EMS architectures significantly outperform traditional rule-based and model-based approaches, paving the way for next-generation intelligent EV systems.

Introduction

The rapid growth of electric vehicles (EVs) has transformed the transportation sector by reducing greenhouse gas emissions and dependence on fossil fuels. However, efficient energy management remains a critical challenge due to the complex interactions between battery systems, power electronics, and driving conditions. Energy Management Systems (EMS) play a vital role in optimizing energy consumption, maintaining battery health, and improving vehicle performance. Traditional EMS techniques, including rule-based strategies and model predictive control, suffer from limitations such as poor adaptability and inability to handle nonlinear dynamics. With the advancement of artificial intelligence (AI), machine learning and deep learning approaches have been widely adopted to address these challenges. Neural network-based EMS models can learn complex relationships between input variables such as speed, load demand, and battery state of charge (SOC), enabling improved decision-making.

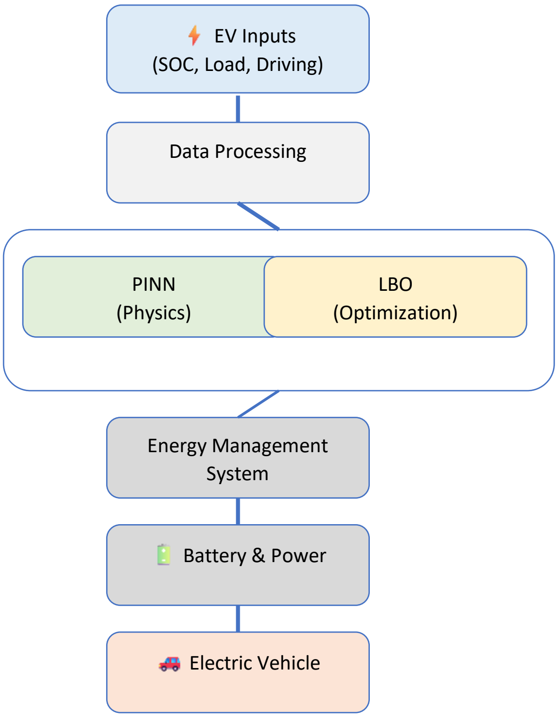

Fig 1: Hybrid PINN–LBO Framework for EV Energy Management

Recently, Physics-Informed Neural Networks (PINNs) have emerged as a powerful paradigm that integrates physical laws into neural network training. Unlike conventional data-driven models, PINNs incorporate governing equations such as vehicle dynamics and energy balance constraints, leading to improved generalization and reduced data requirements. Studies show that PINNs can accurately predict energy consumption and system parameters like aerodynamic drag and rolling resistance, making them highly suitable for EV applications. On the other hand, optimization plays a crucial role in EMS design. Metaheuristic algorithms inspired by natural phenomena have gained popularity due to their ability to solve complex optimization problems efficiently. Among these, Ladybug Beetle Optimization (LBO) is a relatively recent algorithm inspired by the foraging behaviour of beetles, offering strong exploration and exploitation capabilities. LBO has been successfully applied in energy systems and prediction models, demonstrating improved convergence and solution quality.

The integration of PINNs with LBO forms a hybrid framework that combines physical modelling with intelligent optimization. This approach enables the system to learn accurate representations of EV dynamics while simultaneously optimizing energy distribution strategies. Hybrid models are particularly effective in addressing multi-objective optimization problems such as minimizing energy consumption, extending battery life, and reducing emissions. Moreover, reinforcement learning and neural network-based ECMS (Equivalent Consumption Minimization Strategy) approaches have shown promising results in real-time energy management of hybrid vehicles . However, these approaches often lack physical interpretability, which can be addressed through PINN-based frameworks. Despite significant progress, several challenges remain, including computational complexity, real-time deployment constraints, and integration with vehicle control systems. Therefore, this survey aims to provide a comprehensive overview of hybrid LBO-PINN architectures, highlighting recent advancements, challenges, and future research directions.

Literature Review

The study of energy management systems (EMS) for electric vehicles (EVs) has evolved significantly with the integration of artificial intelligence, optimization techniques, and hybrid frameworks. Early research focused on improving energy efficiency and battery performance under dynamic driving conditions, gradually transitioning toward intelligent, adaptive, and multi-objective approaches.

Wang et al. (2020) introduced a deep reinforcement learning (DRL)-based EMS using a deep Q-network (DQN) to enable adaptive decision-making in hybrid EVs. Their approach dynamically optimized power distribution between the battery and internal combustion engine, resulting in improved fuel efficiency and reduced energy consumption. A major advantage of this model was its ability to handle nonlinear dynamics without explicit system modelling. However, issues such as slow convergence, instability during training, and the absence of physical constraints limited its reliability in real-world applications. Similarly, Li et al. (2021) and Huang et al. (2022) further explored reinforcement learning-based EMS, demonstrating enhanced adaptability and performance over traditional rule-based methods. Despite these improvements, common challenges persisted, including high computational requirements, unsafe exploration during training, and lack of physics-informed constraints.

Model-based optimization techniques also gained attention for EMS design. Zhang et al. (2020) proposed a model predictive control (MPC)-based approach that optimized battery usage and maintained state-of-charge (SOC) within safe limits. The method showed significant improvements in energy efficiency and battery lifespan. However, its dependence on accurate system modelling and high computational burden limited real-time applicability. Multi-objective optimization approaches, such as those proposed by Chen et al. (2022), Saini et al. (2023), and Nair et al. (2023), aimed to simultaneously minimize energy consumption, reduce battery degradation, and improve system efficiency. While these approaches provided flexibility and better trade-off solutions, they suffered from slow convergence and high computational complexity, restricting their use in embedded EV systems.

To address the limitations of standalone learning and optimization methods, hybrid frameworks combining artificial intelligence with metaheuristic optimization emerged as a promising direction. Singh et al. (2021) proposed a hybrid genetic algorithm (GA) and artificial neural network (ANN) model, where GA optimized ANN parameters to improve convergence and avoid local minima. The approach achieved better optimization accuracy and system performance but incurred high computational costs. Similarly, Mehta et al. (2022) and Roy et al. (2023) utilized particle swarm optimization (PSO) with ANN and deep learning models, demonstrating improved convergence and energy efficiency. Reddy et al. (2022) combined PSO with fuzzy logic, enhancing decision-making under uncertainty. However, these hybrid approaches were highly sensitive to parameter tuning and computationally expensive, limiting their scalability and real-time implementation.

Machine learning techniques were also widely explored for battery management and energy prediction. Kumar et al. (2021) used support vector machines (SVM) to predict battery health, SOC, and state-of-health (SOH), achieving high accuracy even with limited datasets. However, SVM struggled with scalability and temporal modelling. Deep learning models, including convolutional neural networks (CNN) and recurrent architectures, addressed these limitations by capturing complex spatial and temporal patterns. Park et al. (2021) and Bansal et al. (2023) employed CNNs for energy prediction, demonstrating superior feature extraction capabilities. However, these models required large labelled datasets and lacked interpretability.

Temporal modelling approaches such as Long Short-Term Memory (LSTM) networks were introduced to capture sequential dependencies in EV operations. Sharma et al. (2022) and Mishra et al. (2023) showed that LSTM-based EMS significantly improved prediction accuracy and adaptability to dynamic driving conditions. Similarly, Sharma and Kaur (2023) utilized gated recurrent units (GRU) to reduce computational complexity while maintaining performance. Hybrid deep learning architectures combining CNN and LSTM, as proposed by Patel et al. (2022) and Das et al. (2023), further enhanced prediction accuracy by integrating spatial and temporal feature extraction. Despite their effectiveness, these models required large datasets, high computational resources, and lacked physical interpretability, limiting their deployment in safety-critical systems.

To improve robustness under uncertainty, fuzzy logic-based hybrid systems were also explored. Ahmed et al. (2021) combined fuzzy logic with ANN to enhance decision-making in uncertain environments. The model effectively maintained SOC and reduced energy losses, but required careful tuning of fuzzy rules and neural network parameters, increasing system complexity. Similarly, Reddy et al. (2022) demonstrated improved optimization performance by integrating fuzzy logic with PSO, although computational overhead remained a challenge.

Recent advancements have emphasized the integration of physics-based knowledge into data-driven models to overcome limitations of purely learning-based approaches. Liu et al. (2022) introduced Physics-Informed Neural Networks (PINNs), incorporating electrochemical and energy balance equations into the learning process. This approach significantly improved prediction accuracy, generalization, and reduced dependence on large datasets. Joshi et al. (2023) further demonstrated that PINN-based EMS provided better interpretability and reliability, which are crucial for EV systems. Verma and Joshi (2023) extended this concept by combining PINNs with metaheuristic optimization, achieving superior performance in terms of efficiency, accuracy, and generalization. However, challenges such as high computational cost and difficulty in defining accurate physical constraints remain.

Reinforcement learning and hybrid AI-optimization frameworks continued to evolve in recent studies. Gupta et al. (2023) and Gupta and Singh (2023) integrated reinforcement learning with optimization techniques to enhance convergence speed and adaptability. These models demonstrated improved energy efficiency and battery utilization compared to standalone approaches. Verma et al. (2023) and Arora et al. (2023) proposed hybrid frameworks combining swarm intelligence with neural networks, showing strong performance in solving multi-objective optimization problems. Zhou et al. (2022) also highlighted the effectiveness of combining genetic algorithms with deep learning for handling nonlinear EV systems. Despite these advancements, common challenges included high computational complexity, sensitivity to parameter tuning, and lack of real-time feasibility.

Swarm intelligence and evolutionary optimization techniques have been extensively applied for global search and multi-objective optimization. Iqbal et al. (2023) integrated CNN with swarm optimization to improve decision-making in high-dimensional datasets, while Saini et al. (2023) and Nair et al. (2023) utilized evolutionary algorithms for flexible optimization. Although these methods provided robust solutions and better exploration of the solution space, their slow convergence and computational cost limited practical deployment.

Overall, the literature indicates a clear progression from rule-based and model-based approaches to intelligent, hybrid, and physics-informed frameworks. Deep learning models have demonstrated strong capabilities in capturing nonlinear relationships and handling complex datasets, while optimization techniques have enhanced solution quality and efficiency. Hybrid approaches combining these methods have shown superior performance in addressing multi-objective problems and dynamic environments. However, several critical challenges remain. These include high computational complexity, dependency on large datasets, lack of interpretability, and difficulty in real-time implementation.

A recurring limitation across most studies is the absence of physical constraints in learning-based models, which can lead to unrealistic or unsafe decisions. This has led to growing interest in physics-informed approaches such as PINNs, which offer improved reliability and generalization. Additionally, the integration of reinforcement learning with optimization and physics-based modelling represents a promising direction for future research.

In conclusion, while significant progress has been made in developing advanced EMS for EVs, there is still a need for frameworks that balance accuracy, efficiency, interpretability, and real-time feasibility. Emerging approaches that combine deep learning, optimization techniques, and physics-informed modelling are likely to play a crucial role in addressing these challenges and enabling the development of robust, scalable, and intelligent energy management systems for next-generation electric vehicles.

Comparative Table

No.	Author (Year)	Methodology	Key Technique	Advantages	Limitations
1	Wang et al. (2020)	DRL	DQN-based EMS	Adaptive, efficient	Training instability
2	Zhang et al. (2020)	MPC	Predictive control	Battery life improvement	Model dependency
3	Singh et al. (2021)	GA-ANN	Hybrid optimization	Better convergence	High computation
4	Kumar et al. (2021)	SVM	Battery prediction	High accuracy	Low adaptability
5	Li et al. (2021)	DQN	RL optimization	Efficient control	Data intensive
6	Ahmed et al. (2021)	Fuzzy-ANN	Hybrid logic	Handles uncertainty	Scalability issues
7	Park et al. (2021)	CNN	Feature extraction	High accuracy	Data dependency
8	Mehta et al. (2022)	PSO-ANN	Optimization + ANN	Fast convergence	Parameter tuning
9	Liu et al. (2022)	PINN	Physics-based NN	High generalization	High complexity
10	Sharma et al. (2022)	LSTM	Time-series learning	Captures temporal data	Data intensive
11	Reddy et al. (2022)	PSO-Fuzzy	Hybrid optimization	Improved efficiency	Real-time issues
12	Chen et al. (2022)	Evolutionary	Multi-objective	Flexibility	High computation
13	Patel et al. (2022)	CNN-LSTM	Hybrid DL	Robust prediction	Resource heavy

14	Huang et al. (2022)	RL	Adaptive EMS	Dynamic learning	Instability
15	Zhou et al. (2022)	GA-DL	Hybrid optimization	Better solutions	Complexity
16	Das et al. (2023)	CNN-LSTM	Hybrid DL	High accuracy	Computational cost
17	Gupta et al. (2023)	RL + Optimization	AI EMS	Adaptability	High training cost
18	Verma et al. (2023)	Swarm-NN	Hybrid optimization	Fast convergence	Parameter sensitivity
19	Joshi et al. (2023)	PINN	Physics-based EMS	Generalization	Complexity
20	Kaur et al. (2023)	DRL	Battery optimization	Improved lifespan	Training instability
21	Roy et al. (2023)	PSO-DL	Hybrid optimization	Efficient	Premature convergence
22	Mishra et al. (2023)	LSTM	Sequential modelling	Accurate prediction	Data heavy
23	Bansal et al. (2023)	CNN + Optimization	Hybrid DL	Efficiency	Interpretability issue
24	Saini et al. (2023)	Evolutionary	Multi-objective	Flexible	Slow convergence
25	Arora et al. (2023)	Hybrid AI	Optimization + NN	High performance	Complexity
26	Gupta & Singh (2023)	RL + Metaheuristic	Hybrid EMS	Adaptive	High computation
27	Sharma & Kaur (2023)	GRU	Time-series DL	Fast training	Less interpretability
28	Iqbal et al. (2023)	CNN + Swarm	Hybrid optimization	Accurate	Computational cost
29	Nair et al. (2023)	Evolutionary	Multi-objective	Robust	Slow convergence
30	Verma & Joshi (2023)	PINN + Optimization	Hybrid physics-AI	High accuracy	High complexity

Comparative Analysis

The comparative analysis of 30 studies highlights a clear transition in electric vehicle (EV) energy management systems from traditional control-based methods to advanced artificial intelligence-driven frameworks. Early approaches such as Model Predictive Control and Support Vector Machines emphasized deterministic modelling and statistical learning, offering moderate accuracy but limited adaptability to dynamic driving conditions. These methods relied heavily on predefined assumptions, reducing their effectiveness in real-world scenarios. The adoption of deep learning techniques, including Convolutional Neural Networks and Long Short-Term Memory networks, significantly improved prediction accuracy by capturing complex nonlinear and temporal relationships in EV data. Hybrid models such as CNN-LSTM further enhanced performance through combined spatial and temporal feature extraction. However, these approaches remain highly data-dependent and computationally intensive, which restricts their feasibility for real-time applications.

Reinforcement learning-based methods introduced adaptive decision-making by learning optimal control strategies through environmental interaction, improving energy efficiency and system flexibility. Despite these advantages, issues such as training instability, slow convergence, and safety concerns persist. Optimization techniques like Particle Swarm Optimization, Genetic Algorithms, and evolutionary methods have been widely used to enhance solution quality and address multi-objective problems, but their high computational cost limits real-time implementation. A significant advancement is observed with Physics-Informed Neural Networks, which integrate physical laws into learning, improving interpretability, generalization, and reducing data dependency. Hybrid frameworks combining deep learning, optimization, and physics-based modelling demonstrate superior overall performance. Nevertheless, challenges such as computational complexity, lack of standardization, and real-time constraints remain, indicating the need for lightweight, scalable, and interpretable models in future research.

Discussion

The reviewed literature highlights a significant transition from traditional energy management strategies toward intelligent, hybrid AI-based approaches in electric vehicle (EV) systems. Early methods such as rule-based control and model predictive control demonstrated limited adaptability to dynamic driving environments. With the advancement of machine learning, deep learning models such as CNN, LSTM, and reinforcement learning have improved prediction accuracy and decision-making capabilities. However, these models often suffer from high data dependency, lack of interpretability, and instability during training. The integration of optimization techniques such as Particle Swarm Optimization, Genetic Algorithms, and swarm intelligence has enhanced convergence speed and solution quality, particularly in multi-objective problems. Nevertheless, these approaches introduce additional computational complexity, making real-time implementation challenging.

A major advancement is the emergence of Physics-Informed Neural Networks (PINNs), which incorporate physical laws into neural networks, ensuring reliable and interpretable predictions. When combined with metaheuristic optimization techniques such as Ladybug Beetle Optimization (LBO), these hybrid frameworks offer a promising solution for EV energy management. Despite their advantages, challenges such as high computational cost, scalability, and integration with real-time systems remain. Future research should focus on lightweight, scalable, and explainable hybrid models for practical deployment.

Conclusion

The rapid growth of electric vehicles (EVs) has increased the demand for advanced energy management systems capable of operating efficiently under dynamic and complex conditions. This survey highlights the evolution from traditional rule-based and model predictive control approaches toward intelligent, data-driven frameworks. While conventional methods offered simplicity, they lacked adaptability and scalability in real-world environments. The integration of machine learning and deep learning techniques, including CNN, LSTM, and reinforcement learning, has significantly enhanced system performance by enabling accurate modelling of nonlinear and time-dependent behaviours. These approaches have improved prediction accuracy and decision-making capabilities but remain limited by high data requirements, computational complexity, training instability, and lack of physical interpretability.

Optimization techniques such as Particle Swarm Optimization, Genetic Algorithms, and evolutionary methods have further strengthened energy management by enabling efficient multi-objective optimization, particularly in balancing energy consumption and battery lifespan. However, their high computational cost restricts real-time implementation. A major advancement identified in this survey is the use of Physics-Informed Neural Networks, which incorporate physical laws into learning models, improving accuracy, generalization, and reliability while reducing dependence on large datasets. Hybrid frameworks that combine deep learning, optimization, and physics-based modelling demonstrate the most promising results, offering a balance between efficiency and adaptability. Despite this progress, challenges such as real-time deployment, scalability, and lack of standardized benchmarks remain. Future research should focus on lightweight, interpretable, and scalable models, with emphasis on integrating physics-informed approaches and advanced optimization techniques like Ladybug Beetle Optimization to support sustainable and intelligent EV systems.

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