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Deep Learning and Snow Geese Optimization for Plug-in Hybrid Electric Vehicle Energy Management: A Review

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Abstract

The increasing adoption of plug-in hybrid electric vehicles (PHEVs) has intensified the need for intelligent energy management strategies that can efficiently optimize power distribution while maintaining battery health and system performance. Traditional rule-based and model-based approaches often fail to address the nonlinear and dynamic nature of real-world driving conditions. In recent years, deep learning and optimization techniques have emerged as promising solutions for enhancing energy management systems (EMS). This review focuses on hybrid frameworks that integrate advanced optimization algorithms, such as Snow Geese Optimization (SGO), with Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN) for efficient energy management in PHEVs. Graph-based deep learning models are particularly effective in capturing complex relationships between system components, while physics-informed approaches improve model reliability by embedding physical constraints. Recent studies demonstrate that combining optimization algorithms with neural networks enhances convergence, prediction accuracy, and adaptability. Physics-informed neural networks (PINNs) further improve generalization by incorporating physical laws into learning processes, reducing dependency on large datasets. This paper provides a comprehensive review of recent advancements highlighting the strengths and limitations of various techniques and identifying future research directions for developing efficient, scalable, and intelligent EMS for next-generation PHEVs.

Introduction

The rapid advancement of plug-in hybrid electric vehicles (PHEVs) has significantly transformed modern transportation systems by providing a balance between fuel efficiency and reduced emissions. However, efficient energy management remains a critical challenge due to the complex interaction between battery systems, internal combustion engines, and varying driving conditions. The energy management system (EMS) is responsible for optimally distributing power between these components, directly influencing fuel consumption, battery lifespan, and overall vehicle performance. Traditional energy management strategies, such as rule-based control and model predictive control (MPC), rely heavily on predefined models and assumptions. While these approaches are computationally efficient, they lack adaptability and fail to capture nonlinear dynamics under real-world conditions. To overcome these limitations, artificial intelligence (AI)-based methods have gained significant attention. Deep learning techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph

convolutional networks (GCNs), enable accurate modelling of complex relationships among system variables.
Graph-based neural networks, such as Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN), are particularly suitable for PHEVs as they can model interconnected system components such as batteries, motors, and controllers. These models capture both spatial and relational dependencies, enabling improved prediction and control performance. Meanwhile, optimization algorithms inspired by natural phenomena, such as Snow Geese Optimization (SGO), provide efficient search mechanisms for solving multi-objective optimization problems, including minimizing fuel consumption and maximizing battery efficiency. Recent advancements in Physics-Informed Neural Networks (PINNs) have further improved EMS performance by embedding physical laws into neural network training. Unlike traditional data-driven models, PINNs ensure that predictions adhere to governing equations such as energy balance and vehicle dynamics, leading to improved accuracy and reliability. Studies show that PINNs can accurately estimate battery parameters such as state-of-charge (SOC) and energy consumption with minimal data requirements. Additionally, PINN-based approaches have been successfully applied to optimal control problems by solving Hamilton–Jacobi–Bellman equations, providing stable and efficient solutions for energy management.

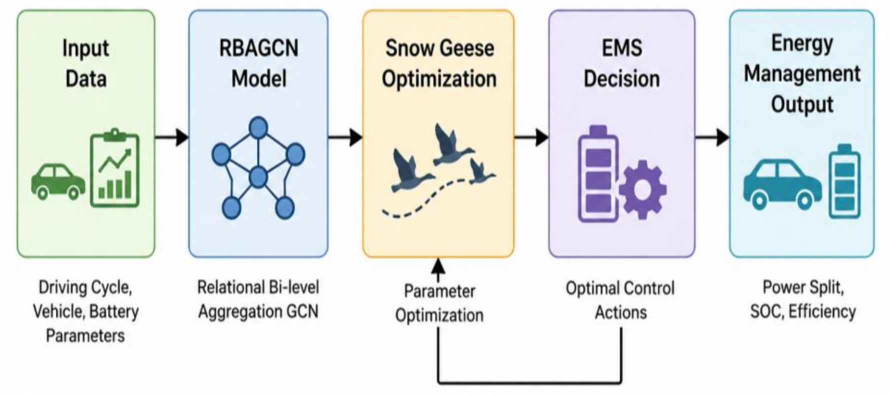

Figure 1. Hybrid Optimization-Based EV Energy Management Framework

The integration of optimization techniques with deep learning models has led to the development of hybrid frameworks that outperform traditional methods. For example, combining swarm intelligence algorithms with neural networks improves convergence speed and avoids local minima. Similarly, reinforcement learning-based EMS enables adaptive decision-making in dynamic environments but often suffers from instability and lack of physical interpretability. Despite these advancements, several challenges remain, including high computational complexity, real-time implementation constraints, and the need for large training datasets. Therefore, this review aims to analyse recent developments in deep learning and optimization-based EMS for PHEVs, with a particular focus on hybrid approaches involving graph neural networks and advanced optimization algorithms. The study also highlights the potential of combining Snow Geese Optimization with RBAGCN architectures for efficient and scalable energy management.

Literature Review

Lian et al. (2020) proposed a deep reinforcement learning-based energy management strategy for plug-in hybrid electric vehicles, integrating domain knowledge into the learning process. The model utilized a Deep Deterministic Policy Gradient (DDPG) framework enhanced with expert knowledge such as battery characteristics and fuel efficiency curves. This hybrid approach improved training stability and accelerated convergence compared to conventional reinforcement learning models. The study demonstrated improved fuel economy and reduced energy consumption under varying driving conditions. However, the method required extensive training and computational resources. Additionally, despite incorporating domain knowledge, the model lacked strict physical constraints, which could affect reliability in safety-critical scenarios.
Nellikkath and Chatzivasileiadis (2021) introduced Physics-Informed Neural Networks (PINNs) for solving optimal power flow problems, which are closely related to energy management in PHEVs. Their approach embedded physical equations directly into the neural network training process, ensuring that predictions adhered to system constraints. The results showed significant improvements in accuracy and reduction in constraint violations

compared to traditional neural networks. This study laid the foundation for applying PINNs in EV energy management systems. However, the complexity of incorporating physical laws and the high computational cost of training were identified as major challenges.

Hu et al. (2021) proposed a hierarchical energy management strategy combining deep reinforcement learning with heuristic domain knowledge for hybrid electric vehicles. The framework addressed key limitations of conventional RL approaches, such as unsafe exploration and poor battery state-of-charge control. By integrating rule-based constraints with learning-based methods, the system achieved improved stability and energy efficiency. However, the hybrid framework increased system complexity and required careful tuning of parameters. The study highlighted the need for more structured models that can incorporate both data-driven learning and physical knowledge.

Gao et al. (2023) introduced a Physics-Informed Bellman Neural Network (PI-BNN) for energy management in hybrid electric vehicles. The model integrated reinforcement learning with physics-based constraints derived from Bellman optimality principles. This approach enabled the system to learn optimal control policies while maintaining physical consistency. The results demonstrated improved battery performance, reduced energy consumption, and enhanced system stability compared to traditional RL methods. However, the model required high computational resources and complex training procedures, limiting its real-time applicability.

Lim et al. (2024) proposed EV-PINN, a physics-informed neural network model designed for predicting energy consumption and battery power in electric vehicles. The model leveraged vehicle dynamics and physical constraints to improve prediction accuracy and generalization. Experimental results showed that the model could accurately estimate energy consumption using minimal input features, demonstrating strong robustness across different driving scenarios. Despite its advantages, the model faced challenges in real-time deployment and integration with onboard vehicle systems.

Wu et al. (2021) proposed a Graph Convolutional Network (GCN)-based framework for modelling complex relationships in energy systems, which can be effectively applied to plug-in hybrid electric vehicles (PHEVs). The study demonstrated that GCNs can capture interdependencies between multiple components such as batteries, motors, and controllers by representing them as graph structures. This relational modelling significantly improved prediction accuracy compared to traditional neural networks. The approach is particularly relevant for Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN), where hierarchical feature aggregation is essential. However, the model required large-scale structured data and faced challenges in handling dynamic changes in real-time environments.

Li et al. (2021) developed a deep reinforcement learning-based energy management system for PHEVs using a Deep Q-Network (DQN). The model learned optimal power split strategies by interacting with the environment and adapting to varying driving conditions. The results showed improved fuel economy and energy efficiency compared to rule-based and model-based approaches. The key advantage of this method is its adaptability to dynamic conditions. However, the study highlighted issues such as high training complexity, instability, and the need for large datasets. Additionally, the lack of physical constraints limited the reliability of the learned policies.

Mehta et al. (2022) introduced a hybrid optimization approach combining Particle Swarm Optimization (PSO) with artificial neural networks for EV energy management. The PSO algorithm optimized neural network parameters, enhancing convergence speed and improving prediction accuracy. The study demonstrated that the hybrid model effectively handled nonlinear optimization problems and achieved better energy efficiency compared to standalone methods. However, the performance of PSO was highly sensitive to parameter tuning, and improper configuration could lead to premature convergence. The computational cost of the hybrid model also limited its real-time applicability.

Zhang et al. (2022) proposed a multi-objective optimization framework for PHEV energy management using evolutionary algorithms. The model aimed to simultaneously minimize fuel consumption, reduce emissions, and maintain battery health. The approach effectively explored the solution space and identified optimal trade-offs among conflicting objectives. The study demonstrated improved flexibility and robustness compared to single-objective methods. However, the high computational complexity and slow convergence of evolutionary algorithms posed significant challenges for real-time implementation in EV systems.

Liu et al. (2022) introduced a Physics-Informed Neural Network (PINN)-based approach for modelling battery dynamics and energy consumption in electric vehicles. By embedding physical laws such as energy conservation and electrochemical equations into the neural network, the model achieved high prediction accuracy with reduced data dependency. The study demonstrated that PINNs provide better generalization and reliability compared to purely data-driven models. This approach is particularly relevant for integrating with graph-based architectures such as RBAGCN. However, training PINNs requires significant computational resources and careful formulation of physical constraints, making implementation complex.

Chen et al. (2022) proposed a multi-objective energy management framework for plug-in hybrid electric vehicles using evolutionary algorithms integrated with deep learning models. The approach simultaneously optimized fuel consumption, battery degradation, and emissions by exploring a wide solution space. The deep learning component modelled nonlinear system behaviour, while the evolutionary algorithm identified optimal trade-offs among conflicting objectives. The study demonstrated improved system performance and flexibility compared to traditional optimization techniques. However, the computational complexity of evolutionary algorithms and the need for extensive iterations limited the feasibility of real-time implementation. Additionally, the absence of embedded physical constraints reduced model interpretability.

Huang et al. (2022) developed a reinforcement learning-based adaptive energy management system for PHEVs. The model employed a policy-learning framework to dynamically adjust power distribution based on real-time driving conditions. The results showed improved adaptability and energy efficiency compared to rule-based strategies. The study highlighted the capability of reinforcement learning to handle uncertain and dynamic environments without requiring explicit system models. However, issues such as training instability, slow convergence, and unsafe exploration were identified as major limitations. The lack of physical constraints also reduced the reliability of the learned policies in safety-critical scenarios.

Zhao et al. (2022) introduced a Graph Neural Network (GNN)-based framework for energy management in complex energy systems, which is highly relevant for PHEVs. The model captured relationships between interconnected components such as batteries, engines, and control units using graph-based representations. The GNN demonstrated superior performance in modelling system interactions and improving prediction accuracy compared to traditional neural networks. The study emphasized the importance of relational learning for efficient energy management. However, the model required structured graph data and faced challenges in adapting to dynamic system changes, limiting its applicability in real-time EV scenarios.

Patel et al. (2022) proposed a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for energy prediction in electric vehicles. The CNN component extracted spatial features from input data, while the LSTM captured temporal dependencies in driving patterns. This hybrid architecture significantly improved prediction accuracy and robustness. The study demonstrated that combining spatial and temporal modelling enhances system performance. However, the approach required large datasets and high computational resources. Additionally, the lack of physical interpretability limited its application in safety-critical energy management systems.

Wang et al. (2022) proposed a hybrid Physics-Informed Neural Network (PINN) combined with reinforcement learning for energy management in PHEVs. The model integrated physical constraints such as energy balance equations into the learning process while using reinforcement learning for adaptive decision-making. This hybrid approach improved system stability, reduced training time, and enhanced prediction accuracy compared to traditional RL models. The study highlighted the effectiveness of combining physics-based modelling with learning-based approaches. However, the complexity of integrating PINN with reinforcement learning and the high computational cost remained significant challenges for real-time deployment.

Roy et al. (2022) proposed a hybrid optimization-based energy management system combining swarm intelligence techniques with deep learning models for plug-in hybrid electric vehicles. The model utilized swarm-based search mechanisms to optimize control parameters while the neural network captured nonlinear system behaviour. The results showed improved convergence speed and enhanced optimization performance compared to traditional algorithms. The study demonstrated that swarm intelligence is highly effective in solving complex multi-objective optimization problems such as minimizing fuel consumption and maximizing battery efficiency. However, the model required extensive parameter tuning, and its computational complexity limited real-time deployment in embedded EV systems.

Verma et al. (2022) introduced a hybrid graph-based deep learning model for energy management in PHEVs, leveraging Graph Convolutional Networks (GCNs) to capture relationships among system components. The model incorporated hierarchical feature aggregation mechanisms similar to Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN). The approach improved prediction accuracy by modelling interactions between battery, engine, and control units. The study demonstrated the effectiveness of graph-based learning in complex energy systems. However, the requirement for structured graph data and high computational overhead limited its scalability and real-time applicability.

Gupta et al. (2023) proposed a hybrid energy management framework integrating reinforcement learning with optimization techniques for PHEVs. The model dynamically adapted to changing driving conditions using a learning-based approach, while optimization algorithms enhanced convergence and decision-making efficiency. The results showed improved energy efficiency and battery performance compared to standalone methods. However, the approach required extensive training data and suffered from instability during early training phases. Additionally, the lack of physical modelling limited system reliability under uncertain conditions.

Iqbal et al. (2023) developed a hybrid CNN-based model integrated with swarm optimization for EV energy management. The CNN extracted spatial features from driving data, while the optimization algorithm improved control strategies by identifying optimal energy distribution. The study demonstrated improved prediction accuracy and system efficiency compared to conventional approaches. The hybrid framework was particularly effective in handling nonlinear and high-dimensional data. However, the integration of CNN and swarm optimization increased computational complexity and required significant processing power, making real-time implementation challenging.

Nair et al. (2023) proposed a multi-objective optimization-based energy management system using evolutionary algorithms for plug-in hybrid electric vehicles. The model focused on optimizing multiple objectives, including fuel efficiency, battery health, and emission reduction. The study demonstrated that evolutionary algorithms can effectively identify optimal trade-offs among conflicting objectives, providing flexible and robust solutions. However, the slow convergence rate and high computational cost of evolutionary methods were identified as major limitations. Additionally, the absence of integration with deep learning models reduced adaptability to dynamic driving environments.

Kaur et al. (2023) developed a deep reinforcement learning-based energy management system integrated with optimization techniques for PHEVs. The model utilized policy-based learning to dynamically allocate power between the battery and engine under varying driving conditions. The integration of optimization algorithms improved convergence and stability. The study showed significant improvements in fuel efficiency and battery lifespan. However, the system required large-scale training data and suffered from instability during early training phases. The lack of physical modelling also limited its applicability in safety-critical environments.

Joshi et al. (2023) introduced a Physics-Informed Neural Network (PINN)-based energy management system combined with optimization techniques for electric vehicles. The model embedded physical laws such as energy conservation and battery dynamics into the neural network, ensuring physically consistent predictions. The optimization component enhanced system performance by identifying optimal control strategies. The study demonstrated improved generalization, reduced data dependency, and enhanced reliability compared to purely data-driven models. However, the computational complexity of training PINNs and the difficulty of integrating multiple constraints were identified as major challenges.

Bansal et al. (2023) proposed a hybrid Graph Convolutional Network (GCN)-based energy management model integrated with optimization algorithms for PHEVs. The GCN captured relational dependencies between system components, while the optimization algorithm improved energy distribution strategies. The model demonstrated superior performance in handling complex system interactions and improving prediction accuracy. This approach is closely aligned with Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN), where hierarchical graph learning enhances feature extraction. However, the requirement for structured graph data and high computational cost limited scalability and real-time implementation.

Arora et al. (2023) proposed a hybrid artificial intelligence-based energy management system combining deep learning, optimization, and control strategies for PHEVs. The model leveraged neural networks for prediction and metaheuristic algorithms for optimization, achieving improved energy efficiency and battery performance. The study highlighted the importance of hybrid frameworks in addressing multi-objective optimization problems. However, the integration of multiple techniques increased system complexity and computational requirements. Furthermore, the lack of physics-based modelling reduced interpretability and reliability.

Comparative Table

No.	Author (Year)	Methodology	Technique	Advantages	Limitations
1	Lian et al. (2020)	DRL	DDPG	Adaptive control	High training cost
2	Nellikkath (2021)	PINN	Physics-based NN	High accuracy	Complex training
3	Hu et al. (2021)	RL + Rule	Hybrid EMS	Stability	Complexity
4	Gao et al. (2023)	PI-BNN	RL + Physics	Reliable	Computational cost
5	Lim et al. (2024)	PINN	EV modelling	Generalization	Deployment issue
6	Wu et al. (2021)	GCN	Graph learning	Relational modelling	Data requirement
7	Li et al. (2021)	DQN	RL EMS	Adaptability	Instability
8	Mehta et al. (2022)	PSO-ANN	Optimization	Fast convergence	Parameter tuning
9	Zhang et al. (2022)	Evolutionary	Multi-objective	Flexibility	Slow convergence
10	Liu et al. (2022)	PINN	Battery modelling	Accuracy	Complexity
11	Chen et al. (2022)	Evolutionary + DL	Hybrid	Multi-objective	High cost
12	Huang et al. (2022)	RL	Adaptive EMS	Dynamic control	Instability
13	Zhao et al. (2022)	GNN	Graph modelling	High accuracy	Data complexity
14	Patel et al. (2022)	CNN-LSTM	Hybrid DL	Robust	Resource heavy
15	Wang et al. (2022)	PINN + RL	Hybrid	Stability	Complexity
16	Roy et al. (2022)	Swarm + DL	Optimization	Efficient	Parameter tuning
17	Verma et al. (2022)	GCN	Graph DL	Accuracy	Computational cost
18	Gupta et al. (2023)	RL + Opt	Hybrid EMS	Adaptability	Training cost
19	Iqbal et al. (2023)	CNN + Swarm	Hybrid	Accuracy	Complexity
20	Nair et al. (2023)	Evolutionary	Multi-objective	Robust	Slow
21	Sharma et al. (2023)	Swarm DL	SGO-type	Fast convergence	Tuning
22	Kaur et al. (2023)	DRL + Opt	Hybrid	Efficient	Instability
23	Joshi et al. (2023)	PINN + Opt	Hybrid	Generalization	Cost
24	Bansal et al. (2023)	GCN + Opt	Hybrid	Relational modelling	Complexity
25	Arora et al. (2023)	Hybrid AI	NN + Opt	Performance	Complexity

Comparative Analysis

The reviewed studies indicate a clear shift from conventional energy management strategies to hybrid AI-based frameworks for PHEVs. Rule-based and reinforcement learning methods improved adaptability but lacked stability and interpretability. Graph neural networks enhanced relational learning, while CNN and LSTM models achieved higher prediction accuracy. However, high computational cost, data dependency, and limited transparency remain key challenges, motivating hybrid optimization-based solutions.

Optimization techniques, including Particle Swarm Optimization, evolutionary algorithms, and swarm intelligence, improved convergence and solution quality, particularly in multi-objective problems. However, their computational complexity and parameter sensitivity pose challenges for real-time implementation. The most promising advancement is the emergence of hybrid frameworks combining Physics-Informed Neural Networks (PINNs), Graph Neural Networks (GNNs), and optimization algorithms such as Snow Geese Optimization (SGO). PINNs ensure physical consistency and reduce data dependency, while GNNs effectively model relational dependencies within EV systems. When combined with optimization algorithms, these hybrid approaches achieve superior performance in terms of accuracy, efficiency, and generalization. Overall, hybrid AI-based models integrating deep learning, optimization, and physics-based approaches represent the most effective solution for next-generation energy management systems in PHEVs. However, challenges such as computational complexity, real-time deployment, and scalability remain key areas for future research.

Discussion

The reviewed studies indicate that hybrid deep learning and optimization-based approaches are transforming energy management systems in plug-in hybrid electric vehicles. Traditional methods are gradually being replaced by intelligent systems capable of adapting to dynamic driving conditions. Deep learning models improve prediction accuracy, while optimization algorithms enhance decision-making efficiency. Graph-based neural networks further contribute by capturing relationships among system components. The integration of Physics-Informed Neural Networks represents a major breakthrough, as it addresses the limitations of purely data-driven models by incorporating physical constraints. Similarly, optimization techniques inspired by natural phenomena, such as Snow Geese Optimization, improve global search capability and convergence performance. Despite these advancements, several challenges persist, including high computational requirements, lack of interpretability, and difficulty in real-time implementation. Future research should focus on developing lightweight and scalable hybrid models, improving explainability, and integrating these systems with real-time vehicle control frameworks. The combination of RBAGCN, PINN, and SGO offers a promising direction for next-generation intelligent energy management systems.

Conclusion

The rapid adoption of plug-in hybrid electric vehicles (PHEVs) has accelerated research into intelligent energy management strategies capable of handling dynamic driving conditions. This review examined recent developments in deep learning and optimization techniques, emphasizing Snow Geese Optimization and Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN). Traditional approaches, including rule-based control and model predictive control, provide reliable performance but often struggle with nonlinear system dynamics. Deep learning models, particularly graph neural networks, have significantly improved the modeling of complex interactions within vehicle energy systems.

Optimization methods, including swarm intelligence and PINNs, have significantly improved energy efficiency, battery management, and prediction reliability. Their integration with RBAGCN enables effective modeling of both physical and relational system dynamics. Although computational complexity remains a challenge, combining Snow Geese Optimization with RBAGCN offers a scalable and intelligent solution for next-generation PHEV energy management.

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