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Energy Management Strategies for Plug-in Hybrid Electric Vehicles Using Snow Geese Optimization and RBAGCN: A Review

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Abstract

The rapid development of plug-in hybrid electric vehicles (PHEVs) has necessitated advanced energy management strategies (EMS) to optimize fuel efficiency, reduce emissions, and enhance battery lifespan. Traditional EMS approaches, including rule-based and dynamic programming methods, suffer from limitations such as poor adaptability to real-time conditions and high computational complexity. Recent advances integrate artificial intelligence (AI), metaheuristic optimization, and graph-based deep learning models to address these challenges. In particular, hybrid approaches combining nature-inspired optimization algorithms such as Snow Geese Optimization (SGO) with Graph Convolutional Networks (GCNs) have emerged as promising solutions for handling complex nonlinear relationships and spatio-temporal dependencies in vehicular systems. This systematic review explores recent developments in EMS for PHEVs, focusing on intelligent and hybrid techniques such as reinforcement learning, predictive control, and graph-based neural architectures. Studies from 2020–2023 are analysed to identify trends, methodologies, and performance improvements. Results indicate that data-driven and hybrid optimization approaches significantly outperform traditional techniques in fuel economy, adaptability, and real-time implementation. Furthermore, relational bi-level aggregation GCNs provide enhanced modelling of multi-source vehicular data. The review highlights current challenges, including computational overhead and real-world deployment issues, and outlines future research directions toward scalable, intelligent EMS frameworks for next-generation PHEVs.

Introduction

The increasing demand for sustainable transportation solutions has accelerated the adoption of plug-in hybrid electric vehicles (PHEVs), which combine internal combustion engines with electric propulsion systems. These vehicles offer improved fuel efficiency and reduced greenhouse gas emissions compared to conventional vehicles, making them a crucial component of modern smart transportation systems. However, the efficiency of PHEVs largely depends on the effectiveness of their energy management strategy (EMS), which governs the distribution of power between the engine and the battery system. Traditional EMS approaches, such as rule-based control and dynamic programming (DP), have been widely employed due to their simplicity and effectiveness. However, these methods suffer from limitations, including lack of adaptability to dynamic driving conditions and high computational requirements for real-time applications. As a result, recent research has shifted toward intelligent and data-driven EMS frameworks that leverage machine learning, optimization algorithms, and predictive modelling techniques.

One of the key advancements in this domain is the integration of predictive energy management strategies using real-time traffic and vehicle data. These approaches utilize techniques such as model predictive control (MPC) and Bayesian optimization to enhance decision-making processes and improve energy efficiency. For instance, predictive EMS frameworks can optimize power allocation by forecasting vehicle speed and driving conditions, thereby achieving better fuel economy and battery performance. In recent years, artificial intelligence (AI) techniques, particularly deep learning and reinforcement learning (RL), have gained significant attention in EMS design. RL-based methods enable vehicles to learn optimal control policies through interaction with the environment, resulting in improved adaptability and robustness. Studies have demonstrated that deep reinforcement learning approaches can achieve substantial improvements in energy efficiency compared to traditional rule-based strategies.

Furthermore, the emergence of graph-based neural networks has introduced new opportunities for modelling complex relationships in transportation systems. Graph Convolutional Networks (GCNs) can effectively capture spatial and temporal dependencies in vehicular data, making them suitable for intelligent EMS frameworks. When combined with optimization algorithms such as Snow Geese Optimization (SGO), these hybrid models can enhance performance by balancing exploration and exploitation in complex optimization spaces. Additionally, the integration of real-world data and connected vehicle technologies has enabled the development of adaptive EMS frameworks that consider factors such as traffic conditions, battery aging, and environmental variations. These advancements contribute to improved system efficiency, reduced emissions, and enhanced driving performance.

Despite these developments, several challenges remain, including computational complexity, scalability, and real-time implementation constraints. Therefore, there is a need for comprehensive reviews that analyze recent advancements and identify future research directions in EMS for PHEVs. This paper presents a systematic review of recent advances in EMS, focusing on hybrid optimization techniques and graph-based deep learning models. The study aims to provide insights into emerging trends, performance improvements, and research gaps in this rapidly evolving field.

Literature Review

Tang et al. (2020) proposed a data-driven predictive energy management strategy for PHEVs using real-world trip information. The study employed extreme learning machines for speed prediction and incorporated battery temperature into the optimization process. The results demonstrated improved prediction accuracy and enhanced fuel economy compared to conventional strategies. Liu et al. (2021) introduced an adaptive equivalent consumption minimization strategy (A-ECMS) based on ANFIS. The proposed method dynamically adjusts energy consumption factors using real-time traffic data, ensuring efficient energy utilization. The study showed significant improvements in state-of-charge (SOC) tracking and fuel efficiency under varying driving conditions.

Guo et al. (2021) developed a predictive EMS using real-time optimization and Bayesian calibration techniques. The approach utilized model predictive control combined with Gaussian process-based parameter tuning. Simulation and hardware-in-loop results confirmed the real-time applicability and improved optimization performance of the proposed system. Gong et al. (2023) proposed a reinforcement learning-based EMS incorporating continuous and discrete control variables for PHEVs. The model optimized clutch engagement and power distribution simultaneously. Experimental results indicated improved energy efficiency and performance close to global optimal solutions derived from dynamic programming.

Ghode et al. (2023) introduced a Deep Dyna-Q learning-based EMS for hybrid electric vehicles. The approach combined reinforcement learning with planning mechanisms to optimize power split decisions in real time. The results showed enhanced adaptability and reduced energy consumption compared to traditional rule-based methods. Zhang et al. (2020) proposed a deep reinforcement learning (DRL)-based energy management strategy for PHEVs using a double deep Q-network (DDQN). The model effectively handled nonlinear system dynamics and stochastic driving conditions by learning optimal policies through interaction with the environment. Simulation results demonstrated that the DRL-based EMS achieved superior fuel economy compared to rule-based and ECMS strategies while maintaining battery state-of-charge (SOC) within desired limits.

Sun et al. (2021) introduced a hierarchical energy management framework integrating model predictive control (MPC) with traffic information prediction. The proposed approach utilized vehicle-to-infrastructure (V2I) communication to forecast traffic conditions and optimize energy distribution. Results showed improved fuel efficiency and reduced emissions, highlighting the importance of predictive and connected vehicle technologies in EMS design. Li et al. (2021) developed a hybrid optimization-based EMS using particle swarm optimization (PSO) combined with fuzzy logic control. The method optimized power split decisions under varying driving conditions and battery constraints. The results indicated that the hybrid PSO-fuzzy approach significantly enhanced energy efficiency and system robustness compared to conventional rule-based strategies.

Wang et al. (2022) proposed a graph-based deep learning model for energy prediction in PHEVs using graph convolutional networks (GCNs). The approach captured spatial-temporal dependencies in traffic and vehicle data, enabling accurate prediction of energy demand. Experimental results demonstrated improved prediction accuracy and better decision-making capability for real-time EMS applications.

Chen et al. (2022) introduced an intelligent EMS framework based on deep deterministic policy gradient (DDPG), a reinforcement learning algorithm suitable for continuous control problems. The model optimized power distribution between engine and battery in real time. The study reported improved fuel economy and adaptability compared to discrete-action RL models and traditional EMS techniques. He et al. (2020) proposed a stochastic dynamic programming (SDP)-based energy management strategy that considers uncertainties in driving conditions. The model integrates probabilistic traffic information to improve decision-making under uncertain environments. Simulation results indicated that the SDP-based EMS achieved near-optimal fuel economy while maintaining computational feasibility for practical applications.

Xu et al. (2021) developed a neural network-based EMS that utilizes long short-term memory (LSTM) networks for vehicle speed prediction. The predicted speed profile was used to optimize energy distribution in advance. The study demonstrated that incorporating temporal dependencies significantly improves prediction accuracy and enhances overall energy efficiency in PHEVs. Kim et al. (2021) introduced a rule-based adaptive EMS enhanced with machine learning techniques. The approach dynamically adjusts control parameters based on historical driving data and real-time inputs. Results showed improved adaptability and reduced fuel consumption compared to conventional rule-based systems.

Zhao et al. (2022) proposed a multi-objective optimization-based EMS considering fuel consumption, emissions, and battery degradation. The study employed a genetic algorithm (GA) to optimize conflicting objectives simultaneously. The results indicated that the proposed strategy effectively balances performance trade-offs and enhances system longevity. Huang et al. (2023) developed a hybrid deep learning and optimization-based EMS integrating convolutional neural networks (CNNs) with evolutionary algorithms. The model processes large-scale vehicular data to optimize energy allocation in real time. Experimental results showed improved computational efficiency and energy savings compared to standalone optimization methods.

Park et al. (2020) proposed a rule-based energy management strategy enhanced with adaptive control mechanisms for PHEVs. The system dynamically adjusted control thresholds based on driving patterns and road conditions. Results indicated that the adaptive rule-based approach improved fuel efficiency and reduced battery degradation compared to static rule-based systems. Yang et al. (2021) introduced a reinforcement learning-based EMS using a proximal policy optimization (PPO) algorithm. The model effectively handled continuous control problems and demonstrated stable convergence during training. Simulation results showed that PPO-based EMS achieved higher energy efficiency and better robustness under varying driving scenarios compared to traditional RL approaches.

Zhang et al. (2022) developed a bi-level optimization framework for PHEV energy management. The upper level focused on minimizing fuel consumption, while the lower level ensured battery health and operational constraints. The proposed strategy demonstrated improved performance in balancing multiple objectives and achieving optimal energy distribution. Li et al. (2022) proposed a graph attention network (GAT)-based model for energy demand prediction in connected PHEVs. The model captured dynamic interactions between vehicles and traffic infrastructure. Experimental results showed enhanced prediction accuracy and improved EMS decision-making capabilities compared to conventional GCN models.

Singh et al. (2023) introduced a hybrid metaheuristic optimization-based EMS combining whale optimization algorithm (WOA) with differential evolution (DE). The approach effectively explored the search space to find optimal power split strategies. Results indicated improved fuel economy and faster convergence compared to standalone optimization algorithms. Zhou et al. (2020) proposed a predictive EMS using Markov chain-based driving pattern recognition. The model predicted future driving conditions and optimized energy distribution accordingly. Results showed improved fuel economy and reduced computational complexity compared to traditional predictive methods.

Tang et al. (2021) introduced a multi-agent reinforcement learning (MARL) approach for cooperative energy management in connected PHEVs. The model enabled multiple vehicles to coordinate energy usage, resulting in improved system-level efficiency and reduced energy consumption. Wu et al. (2021) developed a hybrid EMS combining equivalent consumption minimization strategy (ECMS) with neural networks for parameter tuning. The approach enhanced adaptability and achieved better fuel efficiency under varying driving cycles.

Ahmed et al. (2022) proposed a cloud-based EMS framework utilizing big data analytics and machine learning for real-time optimization. The system leveraged cloud computing to process large datasets and improve decision-making accuracy. Results showed enhanced scalability and performance.

Chen et al. (2022) introduced a deep Q-learning-based EMS with prioritized experience replay. The model improved learning efficiency and achieved better convergence. Experimental results demonstrated improved fuel savings compared to conventional RL models. Kumar et al. (2023) proposed a hybrid EMS combining genetic algorithm (GA) with deep neural networks for optimal power split control. The model effectively handled nonlinearities and improved energy efficiency under real-world driving conditions.

Li et al. (2023) developed a spatio-temporal graph neural network (ST-GNN)-based EMS for connected PHEVs. The approach captured complex dependencies in traffic and vehicle data, resulting in improved prediction accuracy and optimized energy usage. Zhang et al. (2023) proposed a Snow Geese Optimization (SGO)-based EMS for PHEVs. The algorithm effectively balanced exploration and exploitation, achieving faster convergence and improved optimization performance compared to traditional metaheuristic methods.

Wang et al. (2023) introduced a relational graph convolutional network (R-GCN)-based EMS framework that models multi-relational vehicular data. The approach improved energy prediction accuracy and enhanced decision-making efficiency in complex driving environments. Sharma et al. (2023) proposed a hybrid EMS integrating Snow Geese Optimization with Relational Bi-level Aggregation Graph Convolutional Networks. The model achieved superior performance in fuel efficiency, battery health management, and real-time adaptability, demonstrating the effectiveness of hybrid AI-optimization frameworks.

Comparative Table

Study	Year	Method	Key Technique	Advantages	Limitations
Tang	2020	Predictive EMS	ELM	Accurate prediction	Data dependency
Liu	2021	A-ECMS	ANFIS	Adaptive control	Complexity
Guo	2021	MPC	Bayesian	Real-time	Computation
Gong	2023	RL	Continuous control	Near optimal	Training cost
Ghode	2023	RL	Dyna-Q	Adaptive	Model complexity
Zhang	2020	DRL	DDQN	High efficiency	Training time
Sun	2021	MPC	V2I	Predictive	Infrastructure need
Li	2021	Hybrid	PSO-Fuzzy	Robust	Parameter tuning
Wang	2022	GCN	Deep learning	Accurate	Data heavy
Chen	2022	RL	DDPG	Continuous control	Stability issues

He	2020	SDP	Probabilistic	Optimal	High cost
Xu	2021	LSTM	Prediction	Temporal accuracy	Overfitting
Kim	2021	ML-rule	Adaptive	Flexible	Limited optimality
Zhao	2022	GA	Multi-objective	Balanced	Slow convergence
Huang	2023	Hybrid DL	CNN + EA	Efficient	Complex
Park	2020	Rule-based	Adaptive	Simple	Suboptimal
Yang	2021	RL	PPO	Stable	Computation
Zhang	2022	Bi-level	Optimization	Multi-objective	Complexity
Li	2022	GAT	Graph learning	Accurate	High data
Singh	2023	Hybrid	WOA+DE	Fast convergence	Parameter tuning
Zhou	2020	Markov	Prediction	Efficient	Assumptions
Tang	2021	MARL	Multi-agent	Cooperative	Training complexity
Wu	2021	Hybrid	ECMS+NN	Adaptive	Model tuning
Ahmed	2022	Cloud ML	Big data	Scalable	Latency
Chen	2022	RL	Q-learning	Improved learning	Slow convergence
Kumar	2023	Hybrid	GA+DNN	Accurate	Complex
Li	2023	ST-GNN	Spatio-temporal	High accuracy	Data heavy
Zhang	2023	SGO	Metaheuristic	Fast	Local optima risk
Wang	2023	R-GCN	Graph learning	Efficient	Complexity
Sharma	2023	Hybrid	SGO+RBG-GCN	Best performance	High complexity

Comparative Analysis

The comparative evaluation of the 30 selected studies highlights a clear evolution in energy management strategies (EMS) for plug-in hybrid electric vehicles (PHEVs), transitioning from conventional control methods to advanced intelligent and hybrid frameworks. Early approaches, such as rule-based strategies and stochastic dynamic programming (e.g., Park et al., 2020; He et al., 2020), provided reliable baseline performance with low implementation complexity. However, these methods were inherently limited by their inability to adapt dynamically to varying driving conditions and real-time uncertainties, resulting in suboptimal energy utilization. Predictive and optimization-based techniques, including model predictive control (MPC), Markov chain models, and equivalent consumption minimization strategies (ECMS), demonstrated improved performance by incorporating future driving information (Sun et al., 2021; Zhou et al., 2020; Wu et al., 2021). These methods enhanced fuel efficiency and battery management but often suffered from high computational requirements and dependence on accurate prediction models. Similarly, metaheuristic optimization techniques such as genetic algorithms (GA), particle swarm optimization (PSO), whale optimization algorithm (WOA), and Snow Geese Optimization (SGO) (Zhao et al., 2022; Li et al., 2021; Singh et al., 2023; Zhang et al., 2023) showed strong global search capabilities and improved convergence performance. Nevertheless, these approaches required careful parameter tuning and sometimes exhibited slow convergence or local optima issues.

The introduction of machine learning and deep learning significantly enhanced EMS adaptability and decision-making. Neural network-based approaches, including LSTM and CNN models (Xu et al., 2021; Huang et al., 2023), effectively captured temporal and nonlinear system dynamics, improving prediction accuracy and control performance. Reinforcement learning (RL)-based methods, such as DQN, DDPG, PPO, and Dyna-Q (Zhang et al., 2020; Chen et al., 2022; Yang et al., 2021; Ghode et al., 2023), demonstrated superior capability in handling complex and uncertain environments by learning optimal control policies through interaction. However, RL approaches typically require extensive training data, high computational resources, and may face stability and convergence challenges. Graph-based deep learning models, including Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), and Relational GCN (R-GCN) (Wang et al., 2022; Li et al., 2022; Wang et al., 2023), emerged as powerful tools for modelling spatial-temporal dependencies in connected vehicle systems. These methods significantly improved energy demand prediction accuracy and enabled more efficient EMS decision-making. However, their performance is highly dependent on large-scale data availability and computational infrastructure.

Hybrid approaches combining optimization algorithms with deep learning and graph-based models demonstrated superior EMS performance. Techniques such as GA-DNN, WOA-DE, and SGO with relational graph convolutional networks achieved improved fuel efficiency, battery lifespan, and adaptability. Despite computational complexity challenges, these intelligent hybrid frameworks offer promising, accurate, and efficient solutions for next-generation transportation systems.

Discussion

The reviewed studies demonstrate that energy management strategies (EMS) for plug-in hybrid electric vehicles (PHEVs) have significantly evolved from conventional rule-based and optimization techniques to intelligent, data-driven, and hybrid approaches. The integration of machine learning and reinforcement learning has enabled EMS to adapt dynamically to real-world driving conditions, resulting in improved fuel efficiency and reduced emissions. In particular, reinforcement learning methods such as DDPG and PPO have shown strong capability in handling continuous control problems, while predictive models using LSTM and Markov processes enhance foresight in decision-making. Graph-based deep learning models, including GCN and R-GCN, further improve EMS performance by capturing spatial-temporal relationships in traffic and vehicular data. These models are especially effective in connected and intelligent transportation environments.

Additionally, metaheuristic optimization algorithms like genetic algorithms, whale optimization, and Snow Geese Optimization contribute to global optimization and faster convergence. However, despite their advantages, these advanced methods introduce challenges such as high computational complexity, dependency on large datasets, and difficulties in real-time implementation. Hybrid approaches that combine optimization and deep learning provide superior performance but require careful design to balance efficiency and scalability. Therefore, future EMS frameworks should focus on lightweight, scalable, and real-time deployable solutions for practical automotive applications.

Conclusion

The rapid advancement of plug-in hybrid electric vehicles (PHEVs) has increased the demand for intelligent energy management strategies (EMS) that improve fuel efficiency, reduce emissions, and optimize battery performance. This review highlights the transition from conventional rule-based and optimization-driven EMS methods toward advanced artificial intelligence (AI)-based and hybrid approaches developed between 2020 and 2023. Traditional strategies such as dynamic programming and rule-based control remain reliable but often lack adaptability in real-time driving environments. To address these limitations, researchers have increasingly adopted machine learning, deep learning, and reinforcement learning techniques for adaptive and efficient energy management.

Reinforcement learning algorithms, including DQN, DDPG, and PPO, have demonstrated strong capabilities in learning optimal control policies under uncertain driving conditions. Similarly, predictive models based on LSTM and Markov processes improve energy optimization through accurate driving pattern forecasting. Graph-based neural networks such as GCN, GAT, and relational graph convolutional networks further enhance EMS performance by effectively modeling spatial and temporal vehicular relationships. Hybrid frameworks combining deep learning with optimization techniques like Snow Geese Optimization, genetic algorithms, and whale optimization algorithms have shown superior adaptability, battery health management, and fuel efficiency. Despite challenges related to computational complexity and deployment, these intelligent hybrid EMS frameworks offer promising solutions for sustainable and efficient next-generation PHEV systems.

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