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A Comprehensive Review of Energy Management Strategy for Plug-in Hybrid Electric Vehicles Using Snow Geese Optimization and Relational Bi-level Aggregation Graph Convolutional Network

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Abstract

Energy management strategies (EMS) play a critical role in enhancing the efficiency, fuel economy, and emission reduction of plug-in hybrid electric vehicles (PHEVs). With the increasing demand for sustainable transportation, intelligent optimization techniques and deep learning models have gained significant attention in EMS design. This paper presents a comprehensive review of an advanced EMS framework that integrates Snow Geese Optimization (SGO) and Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN). The proposed hybrid approach aims to optimize power distribution between internal combustion engines and electric motors while capturing complex relational dependencies among vehicle states. Traditional EMS approaches, including rule-based and dynamic programming methods, often suffer from scalability and real-time implementation challenges. In contrast, modern AI-based techniques such as reinforcement learning and graph neural networks provide adaptive and data-driven solutions. Studies show that incorporating driving conditions and intelligent learning mechanisms can significantly improve energy efficiency and reduce fuel consumption in PHEVs. Furthermore, neural network-based EMS models have demonstrated strong generalization capabilities across diverse driving cycles. This review highlights recent advancements, challenges, and future directions in integrating bio-inspired optimization algorithms with graph-based deep learning architectures for efficient and intelligent energy management in next-generation hybrid vehicles.

Introduction

The rapid growth of global energy consumption and environmental concerns has accelerated the development of sustainable transportation technologies. Among these, plug-in hybrid electric vehicles (PHEVs) have emerged as a promising solution due to their ability to combine the advantages of conventional internal combustion engines and electric propulsion systems. A PHEV operates using both fuel and electricity, allowing it to reduce greenhouse gas emissions and improve fuel efficiency compared to traditional vehicles. However, the performance of PHEVs heavily depends on the effectiveness of their energy management strategies (EMS), which determine how energy is distributed between different power sources under varying driving conditions. Energy management strategies are designed to optimize fuel consumption, battery usage, and emission levels while maintaining vehicle performance. Conventional EMS approaches include rule-based strategies, equivalent consumption minimization strategies (ECMS), and dynamic programming (DP). While these methods provide acceptable performance, they often lack adaptability and real-time optimization capabilities, particularly under complex and dynamic driving scenarios. Optimization-based methods, such as particle swarm optimization (PSO), have been introduced to address these limitations by minimizing total energy cost and improving system efficiency. Nevertheless, these techniques still face challenges related to computational complexity and scalability.

Recent advancements in artificial intelligence have led to the development of data-driven EMS approaches. Machine learning and deep learning models, including reinforcement learning and neural networks, enable adaptive decision-making by learning from historical and real-time data. For instance, reinforcement learning-based EMS can dynamically adjust control policies based on driving conditions, resulting in improved fuel efficiency and reduced emissions. Similarly, neural network-based strategies have shown the ability to generalize across different driving cycles and optimize energy distribution effectively. In addition to machine learning techniques, bio-inspired optimization algorithms have gained popularity in solving complex optimization problems in EMS. The Snow Geese Optimization (SGO) algorithm, inspired by the migratory behaviour of snow geese, offers efficient global search capabilities and robustness in dynamic environments. By integrating such optimization techniques with advanced deep learning models, it is possible to achieve superior performance in energy management.

Graph-based deep learning approaches, particularly Graph Convolutional Networks (GCNs), have recently been introduced to model relational dependencies among different components of PHEVs. The Relational Bi-level Aggregation Graph Convolutional Network (RBAGCN) extends traditional GCNs by capturing hierarchical and relational interactions between system variables, enabling more accurate and context-aware decision-making. This is particularly useful in PHEVs, where multiple subsystems, including the battery, engine, and driving environment, interact in complex ways. Furthermore, modern EMS frameworks are increasingly incorporating real-world data, connectivity, and cloud-based intelligence. Data-driven approaches that leverage real-world trip information have demonstrated improvements in energy efficiency by learning optimal control policies from historical driving patterns. These advancements highlight the shift toward intelligent, adaptive, and connected EMS solutions.

Despite significant progress, several challenges remain, including real-time implementation, computational overhead, model interpretability, and integration with emerging technologies such as vehicle-to-grid (V2G) systems. Therefore, there is a need for comprehensive research that combines optimization algorithms, deep learning techniques, and graph-based models to develop efficient and scalable EMS solutions. This paper aims to provide a comprehensive review of energy management strategies for PHEVs, focusing on the integration of Snow Geese Optimization and Relational Bi-level Aggregation Graph Convolutional Networks. The study explores recent developments, identifies research gaps, and discusses future directions for intelligent energy management in hybrid electric vehicles.

Literature Review

A comprehensive body of research on energy management strategies (EMS) for plug-in hybrid electric vehicles (PHEVs) highlights a rapid transition from conventional rule-based control methods toward intelligent, optimization-driven, and learning-based frameworks designed to improve fuel efficiency, reduce emissions, and enhance battery performance under diverse driving conditions. Early adaptive approaches focused on rule-based EMS enhanced with real-time driving pattern recognition, where Sharma et al. proposed a system that classified driving modes such as urban, suburban, and highway using machine learning classifiers and dynamically adjusted control rules accordingly, achieving improved fuel economy but limited by classification accuracy and lack of global optimality. In parallel, model predictive control (MPC) approaches gained attention, as demonstrated by Zhou et al., who incorporated stochastic driving behavior into MPC to account for uncertainty in traffic and driver actions, resulting in smoother energy transitions and improved robustness, although at the cost of high computational complexity and reliance on accurate probabilistic modeling. Li et al. advanced the ECMS framework by integrating predictive control using navigation-based future driving information, combining MPC with ECMS to anticipate load demands and optimize energy distribution, achieving improved fuel economy and emission reduction while highlighting dependency on prediction accuracy for real-world effectiveness.

As computational intelligence methods matured, optimization-based EMS became prominent. Wang et al. combined particle swarm optimization (PSO) with dynamic programming (DP) to achieve global optimality while balancing computational complexity, where PSO identified optimal control parameters and DP refined them, yielding reduced fuel consumption and battery degradation, though constrained by offline computation requirements. Similarly, Kumar et al. introduced a bio-inspired metaheuristic algorithm that improved global search capability and avoided local minima, outperforming genetic algorithms and PSO in convergence and solution quality, yet requiring careful parameter tuning and showing sensitivity to initialization. Das et al. and Choudhary et al. further explored ant colony optimization (ACO) and multi-objective genetic algorithms (MOGA), respectively, addressing fuel consumption, emissions, and battery degradation simultaneously, but facing computational burdens that limited real-time implementation. Verma et al. extended swarm intelligence approaches inspired by collective animal behavior, achieving fast convergence and global optimization, though performance depended heavily on parameter selection and initial conditions.

With the advancement of data-driven methods, deep learning emerged as a transformative tool for EMS. Chen et al. developed a deep neural network (DNN)-based EMS that learned nonlinear relationships between vehicle states, driving patterns, and energy consumption from historical data, enabling near-optimal real-time decisions with reduced computational cost, although performance depended on dataset quality. Patel et al. proposed a hybrid convolutional neural network (CNN) and long short-term memory (LSTM) architecture, where CNN extracted spatial features and LSTM captured temporal dependencies in driving data, resulting in improved fuel efficiency and emission reduction, albeit with increased computational complexity. Iqbal et al. utilized recurrent neural networks (RNNs) to predict future energy demand based on sequential driving patterns, improving prediction accuracy but facing challenges related to overfitting and data dependency. Banerjee et al. further developed CNN-based hybrid models that improved feature extraction efficiency while reducing computational overhead compared to deeper architectures, though requiring extensive training data.

Reinforcement learning (RL) emerged as one of the most promising directions due to its ability to learn optimal control policies through environmental interaction without explicit system modeling. Huang et al. introduced policy gradient-based EMS capable of continuous control optimization, improving fuel economy and battery efficiency but requiring extensive training time. Liu et al. proposed a Twin Delayed Deep Deterministic Policy Gradient (TD3)-based EMS that addressed overestimation bias in traditional actor-critic methods, improving stability and convergence while reducing battery degradation, though requiring high computational resources. Park et al. extended Deep Deterministic Policy Gradient (DDPG) for continuous power split control, enabling smooth energy distribution and strong generalization across driving cycles, but requiring careful hyperparameter tuning. Mehta et al. developed adaptive dynamic programming (ADP) approaches using value function approximation, improving real-time adaptability and reducing computational burden compared to dynamic programming, though accuracy depended on approximation quality. Nair et al. introduced transfer learning-based RL, improving learning efficiency across new driving environments, though transferability across highly diverse conditions remained limited.

Further advancements include multi-agent reinforcement learning (MARL), as proposed by Tan et al., where multiple agents controlled different vehicle components collaboratively, improving scalability and system efficiency but introducing coordination and convergence challenges. Gupta et al. combined autoencoders with reinforcement learning, where autoencoders reduced feature dimensionality and RL optimized control policies, improving efficiency and scalability but increasing system complexity. Ahmed et al. integrated genetic algorithms (GA) with neural networks, where GA optimized network parameters and neural networks handled real-time decision-making, improving energy distribution accuracy but increasing computational overhead. Roy et al. combined fuzzy logic with neural networks to handle uncertainty while improving learning capability, though system integration remained complex.

Graph-based learning methods have recently emerged as a powerful paradigm for EMS due to their ability to model structural dependencies among vehicle components. Zhao et al. introduced Graph Convolutional Networks (GCNs) to capture spatial and temporal relationships among battery state-of-charge, engine load, and driving behavior, improving adaptability and energy efficiency but requiring large datasets and high computational resources. Sun et al. enhanced graph learning with attention mechanisms, prioritizing critical features and improving decision accuracy in dynamic environments, though increasing model complexity. Kulkarni et al. proposed Graph

Attention Networks (GATs), improving energy optimization performance compared to GCNs but facing real-time deployment challenges due to computational demands. Kapoor et al. further developed bi-level optimization integrated with GCNs, modeling hierarchical energy relationships and improving accuracy and adaptability, although interpretability and computational cost remained concerns.

Hybrid EMS frameworks that combine multiple methodologies have demonstrated the most promising results by leveraging complementary strengths. Singh et al. integrated fuzzy logic with machine learning to improve interpretability and robustness under uncertainty, achieving real-time applicability but requiring expert-defined rule structures. Yang et al. proposed hierarchical EMS combining rule-based control with optimization layers, balancing real-time feasibility and global optimality but increasing system design complexity. Sun et al. combined graph neural networks with attention mechanisms, enhancing spatial-temporal learning for energy optimization. Ahmed et al. and Gupta et al. developed hybrid GA-neural and autoencoder-RL systems respectively, improving performance but increasing training complexity. Kapoor et al. demonstrated that combining graph convolutional learning with bi-level optimization significantly improves EMS performance across multiple objectives.

Despite these advancements, several persistent challenges remain, including high computational cost, data dependency, lack of interpretability, and difficulty in real-time implementation. Many advanced models require extensive training data and computational resources, limiting their deployment in embedded automotive systems. Additionally, ensuring robustness under highly variable driving conditions and maintaining battery longevity remain critical concerns. Future EMS research is expected to focus on lightweight, scalable, and interpretable AI models capable of real-time operation. Integration with connected vehicle systems, vehicle-to-grid (V2G) technology, and edge computing is expected to further enhance energy optimization capabilities. Emerging approaches such as Snow Geese Optimization combined with relational bi-level aggregation graph convolutional networks represent a promising direction, offering improved global optimization, structural learning, and adaptive decision-making for next-generation intelligent and sustainable PHEV energy management systems.

Comparative Table

Study	Year	Method	Technique Used	Key Contribution	Limitation
Zhang et al.	2020	RL	DQN	Adaptive EMS	High training cost
Li et al.	2020	Optimization	ECMS + MPC	Predictive control	Depends on prediction
Wang et al.	2021	Hybrid	PSO + DP	Global optimization	Not real-time
Chen et al.	2021	Deep Learning	DNN	Real-time EMS	Data dependency
Kumar et al.	2022	Bio-inspired	Metaheuristic	Better convergence	Parameter tuning
Liu et al.	2022	RL	TD3	Stable learning	High computation
Zhao et al.	2022	GNN	GCN	Relational modeling	Complex training
Singh et al.	2023	Hybrid	Fuzzy + ML	Interpretability	Scalability issue
Patel et al.	2023	Deep Learning	CNN-LSTM	Temporal modeling	High complexity
Reddy et al.	2023	Optimization	Multi-objective	Trade-off solutions	Computational cost
Sharma et al.	2020	Rule-based	ML classifier	Real-time EMS	Limited optimality
Zhou et al.	2020	MPC	Stochastic MPC	Robust EMS	High complexity
Huang et al.	2021	RL	Policy Gradient	Continuous control	Long training
Yang et al.	2021	Hybrid	Hierarchical	Balanced approach	Design complexity
Ahmed et al.	2022	Hybrid	GA + NN	Improved accuracy	High overhead
Park et al.	2022	RL	DDPG	Continuous control	Hyperparameter tuning

Sun et al.	2022	GNN	Attention-GNN	Improved accuracy	Resource intensive
Verma et al.	2023	Swarm	SI algorithm	Fast convergence	Sensitive parameters
Gupta et al.	2023	Hybrid	Autoencoder + RL	Efficient learning	Complex integration
Tan et al.	2023	RL	Multi-agent RL	Scalability	Coordination issue
Mehta et al.	2020	ADP	Value function	Real-time EMS	Approximation error
Roy et al.	2021	Hybrid	Fuzzy + NN	Adaptive EMS	Design complexity
Das et al.	2021	Optimization	ACO	Better solutions	High computation
Iqbal et al.	2022	Deep Learning	RNN	Prediction accuracy	Overfitting
Choudhary et al.	2022	Optimization	MOGA	Multi-objective	Slow computation
Banerjee et al.	2023	Deep Learning	CNN	Efficient EMS	Data requirement
Kulkarni et al.	2023	GNN	GAT	Attention modeling	High complexity
Nair et al.	2023	RL	Transfer Learning	Faster learning	Limited transferability
Bose et al.	2023	Bio-inspired	SGO	Global optimization	Parameter tuning
Kapoor et al.	2023	Hybrid	GCN + Bi-level	Advanced EMS	Computational cost

Comparative Analysis

The comparative analysis of the reviewed studies reveals a significant evolution in energy management strategies for plug-in hybrid electric vehicles from conventional rule-based methods to advanced artificial intelligence and optimization-driven approaches. Early methods such as rule-based and ECMS strategies provided simplicity and real-time feasibility but lacked adaptability and global optimality. Optimization-based techniques, including PSO, GA, and ACO, improved energy efficiency and convergence but were often computationally intensive and unsuitable for real-time deployment. The emergence of reinforcement learning methods, such as DQN, DDPG, and TD3, introduced adaptive and data-driven decision-making capabilities, enabling systems to learn optimal policies under dynamic conditions.

However, these methods require extensive training and computational resources. Deep learning approaches, including CNN, LSTM, and RNN, further enhanced predictive capabilities by capturing temporal and nonlinear relationships in driving data. Graph-based models such as GCNs and GATs represent a recent advancement, enabling relational modelling of vehicle components and improving decision accuracy. Additionally, bio-inspired algorithms like Snow Geese Optimization demonstrated strong global search capabilities and robustness. Hybrid approaches combining optimization, machine learning, and graph-based models have shown the most promising results by balancing efficiency, adaptability, and scalability. Despite these advancements, challenges such as computational complexity, real-time implementation, and model interpretability remain critical research gaps.

Discussion

The reviewed literature highlights the rapid advancement of intelligent energy management strategies for plug-in hybrid electric vehicles, driven by the integration of artificial intelligence, optimization algorithms, and data-driven approaches. Traditional rule-based and optimization-based methods have laid the foundation for EMS design; however, their limitations in handling dynamic and uncertain driving conditions have led to the adoption of advanced techniques such as reinforcement learning and deep learning. These modern approaches enable adaptive and predictive control, significantly improving fuel efficiency and reducing emissions. The incorporation of graph neural networks further enhances the capability of EMS by modelling complex relationships among vehicle components.

Additionally, bio-inspired optimization algorithms, such as Snow Geese Optimization, provide efficient global search mechanisms, improving solution quality. Despite these advancements, several challenges remain, including high computational requirements, data dependency, and difficulties in real-time implementation. Furthermore, the interpretability of complex AI models is a critical concern for practical deployment in automotive systems. Future research should focus on developing lightweight, interpretable, and scalable EMS solutions that can operate efficiently in real-time environments. The integration of emerging technologies such as vehicle-to-grid systems and connected vehicle infrastructure also presents new opportunities for improving energy management in next-generation hybrid vehicles.

Conclusion

Energy management strategies (EMS) are essential for improving the efficiency, performance, and sustainability of plug-in hybrid electric vehicles (PHEVs). This review explores a broad range of EMS approaches, highlighting the shift from conventional control methods to advanced artificial intelligence and optimization-driven techniques. Traditional methods such as rule-based control and equivalent consumption minimization strategies (ECMS) are widely used due to their simplicity and ease of implementation, but they often lack adaptability and struggle to achieve global optimal performance under varying driving conditions. To address these limitations, optimization techniques like particle swarm optimization (PSO), genetic algorithms (GA), and ant colony optimization (ACO) have been adopted, offering improved energy efficiency and better fuel–battery trade-off through global search capabilities, though they are often limited by high computational complexity and reduced real-time applicability.

More recently, artificial intelligence-based methods have gained significant attention, particularly reinforcement learning approaches such as DQN, DDPG, and TD3, which enable adaptive decision-making in dynamic environments. Deep learning models including CNN, LSTM, and RNN further enhance prediction accuracy and system responsiveness. In addition, graph-based techniques like graph convolutional networks (GCNs) and graph attention networks (GATs) provide improved modeling of complex interactions within vehicle energy systems. Hybrid frameworks that combine optimization algorithms, deep learning, and graph-based learning demonstrate the strongest overall performance. However, challenges such as computational cost, data dependency, interpretability, and real-time deployment still remain. Future research should focus on lightweight, scalable, and real-time EMS solutions, with promising directions emerging from the integration of Snow Geese Optimization and relational bi-level aggregation graph convolutional networks for intelligent and sustainable PHEV energy management.

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