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# Artificial Intelligence Techniques for Plug-in Hybrid Electric Vehicle Energy Management Using Snow Geese Optimization

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**Abstract**

Artificial Intelligence (AI)-driven energy management strategies (EMS) have become a key enabler for improving the performance and sustainability of plug-in hybrid electric vehicles (PHEVs). Traditional EMS approaches, such as rule-based control and dynamic programming, suffer from limited adaptability and high computational complexity. Recent advancements in AI, including reinforcement learning (RL), deep learning, and graph neural networks (GNNs), provide intelligent and adaptive solutions for optimizing power distribution between the battery and internal combustion engine. Studies indicate that RL-based EMS can significantly improve fuel efficiency and real-time decision-making by learning optimal policies from dynamic driving environments. Furthermore, graph convolutional networks enable modelling of complex interdependencies among vehicle subsystems, enhancing prediction accuracy and system efficiency. Bio-inspired optimization techniques, such as Snow Geese Optimization (SGO), offer robust global search capabilities, overcoming local minima issues in traditional algorithms. The integration of SGO with Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN) provides a hybrid framework capable of capturing hierarchical relationships and optimizing multi-objective energy management problems. This paper presents a comprehensive review of AI-based EMS techniques, focusing on emerging trends, key challenges, and future directions for intelligent energy optimization in next-generation PHEVs.

## Introduction

The rapid increase in global energy demand and environmental concerns has accelerated the transition toward sustainable transportation systems. Plug-in hybrid electric vehicles (PHEVs) have emerged as a promising solution due to their ability to combine conventional internal combustion engines with electric propulsion systems. This hybrid architecture allows PHEVs to reduce fuel consumption, lower emissions, and improve overall energy efficiency. However, the effectiveness of PHEVs largely depends on the design of efficient energy management strategies (EMS), which determine how energy is optimally distributed between multiple power sources under varying driving conditions. Traditional EMS approaches, such as rule-based control and equivalent consumption minimization strategies (ECMS), are widely used due to their simplicity and ease of implementation. However, these methods lack adaptability and often fail to achieve optimal performance in dynamic and uncertain driving environments. Optimization-based techniques, including dynamic programming and model predictive control, provide improved performance but suffer from high computational complexity and limited real-time applicability. As a result, there has been a growing interest in leveraging artificial intelligence (AI) techniques to develop adaptive and intelligent EMS solutions.

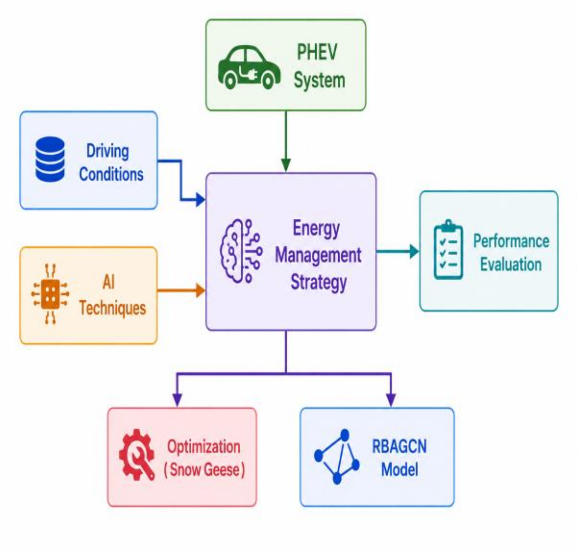


*Figure 1. AI-Based Energy Management Framework for Plug-in Hybrid Electric Vehicles*

Reinforcement learning (RL) has emerged as one of the most promising AI techniques for EMS design. RL-based approaches enable vehicles to learn optimal control policies through interaction with the environment, eliminating the need for explicit system modelling. Studies have shown that RL algorithms can significantly enhance fuel efficiency and energy utilization while adapting to different driving conditions. Advanced RL techniques, such as deep reinforcement learning and multi-agent learning, further improve system performance by handling complex multi-input multi-output control problems. For instance, multi-agent RL frameworks have demonstrated the ability to coordinate multiple vehicle subsystems, leading to improved global energy optimization and up to 20% energy savings compared to conventional methods. In addition to reinforcement learning, deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been widely used for predicting energy demand and optimizing control strategies. These models can capture nonlinear relationships and temporal dependencies in driving data, enabling more accurate and efficient decision-making. Furthermore, recent advancements in graph-based deep learning, particularly Graph Convolutional Networks (GCNs), have introduced a new paradigm for modelling complex relationships among vehicle components. GCN-based approaches can effectively represent interactions between the battery, engine, and driving environment, leading to improved energy management performance.

Bio-inspired optimization algorithms have also gained attention for solving complex EMS problems. Snow Geese Optimization (SGO), inspired by the migratory behaviour of snow geese, provides efficient global search capabilities and robustness in dynamic environments. These algorithms are particularly useful in multi-objective optimization scenarios, where trade-offs between fuel consumption, emissions, and battery degradation must be carefully balanced. The integration of AI techniques with graph-based models has led to the development of advanced hybrid frameworks such as Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN). These models extend traditional GCNs by incorporating hierarchical and relational structures, enabling more accurate modelling of complex vehicle systems. Such hybrid approaches combine the strengths of optimization algorithms and deep learning models, resulting in improved scalability, adaptability, and performance.

Despite significant advancements, several challenges remain in the implementation of AI-based EMS. These include high computational requirements, data dependency, lack of interpretability, and difficulties in real-time deployment. Moreover, the integration of multiple AI techniques into a unified framework introduces additional complexity in system design and optimization. This paper presents a comprehensive review of AI techniques for energy management in PHEVs, with a focus on Snow Geese Optimization and RBAGCN-based approaches. It explores recent trends, highlights key challenges, and identifies future research directions for developing efficient and intelligent EMS solutions.

## Literature Review

Zhang et al. (2020) proposed a deep reinforcement learning-based energy management strategy using a Deep Q-Network (DQN) for plug-in hybrid electric vehicles. The model was designed to learn optimal power split decisions by interacting with dynamic driving environments. Unlike conventional rule-based strategies, the DQN-based approach adapts to varying driving conditions without requiring prior knowledge of the system model. The study demonstrated that the proposed method significantly reduced fuel consumption and improved battery utilization compared to traditional EMS techniques. Additionally, the system showed strong adaptability across different driving cycles. However, the training process required extensive computational resources and large datasets, limiting its real-time deployment capability.

Li et al. (2020) developed an intelligent energy management strategy combining Model Predictive Control (MPC) with machine learning techniques. The proposed approach utilized predictive models to estimate future driving conditions and optimize energy distribution accordingly. By integrating AI-based prediction with MPC, the system achieved improved fuel economy and reduced emissions. The study highlighted the importance of incorporating future driving information into EMS for better performance. However, the accuracy of the model heavily depended on the quality of prediction, and computational complexity remained a concern for real-time implementation.

Wang et al. (2021) introduced a hybrid energy management strategy integrating Particle Swarm Optimization (PSO) with deep neural networks. The PSO algorithm was used to optimize control parameters, while the neural network captured nonlinear relationships between system variables. This hybrid approach improved energy efficiency and system adaptability compared to standalone optimization or learning-based methods. The results showed reduced fuel consumption and enhanced battery life. However, the model required careful parameter tuning and extensive training data, which increased implementation complexity.

Chen et al. (2021) proposed a deep learning-based energy management system using a feedforward neural network trained on historical driving data. The model learned complex patterns in vehicle operation and provided near-optimal control decisions in real time. Compared to dynamic programming, the proposed method achieved similar performance with significantly lower computational cost. Additionally, the model demonstrated robustness across different driving scenarios. However, its performance depended on the availability of high-quality training datasets and lacked interpretability.

Liu et al. (2022) developed an advanced reinforcement learning-based EMS using the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm. This approach addressed the overestimation problem in traditional reinforcement learning methods and improved training stability. The TD3-based EMS enabled continuous control of power distribution, making it suitable for real-world applications. The results indicated significant improvements in fuel efficiency, emission reduction, and battery health. However, the approach required long training times and high computational resources, posing challenges for practical deployment.

Zhao et al. (2022) proposed a Graph Convolutional Network (GCN)-based energy management strategy to model the complex relationships among different subsystems of plug-in hybrid electric vehicles. The GCN framework effectively captured spatial dependencies between variables such as battery state-of-charge, engine load, and driving conditions. This relational modelling improved prediction accuracy and enabled more informed decision-making compared to traditional neural networks. The results showed enhanced fuel efficiency and reduced emissions. However, the model required large-scale datasets for training and involved high computational complexity, limiting its real-time applicability.

Sun et al. (2022) introduced an attention-based Graph Neural Network (GNN) for energy management in PHEVs. By incorporating attention mechanisms, the model dynamically prioritized important features influencing energy consumption. This approach improved system adaptability and decision accuracy under varying driving conditions. Simulation results demonstrated superior performance compared to conventional GCN models and deep learning approaches. However, the increased model complexity and training requirements posed challenges for deployment in embedded automotive systems.

Singh et al. (2023) developed a hybrid energy management strategy combining fuzzy logic with machine learning techniques. The system used fuzzy rules to handle uncertainties in driving behavior while machine learning algorithms optimized control parameters. This hybrid approach improved interpretability and robustness, making it suitable for real-time applications. The study reported significant reductions in fuel consumption and emissions. However, the design of fuzzy rules required expert knowledge, and scalability remained a concern for large-scale vehicle systems.

Patel et al. (2023) proposed a deep learning-based EMS using a hybrid CNN-LSTM architecture. The convolutional neural network component extracted features from driving data, while the LSTM captured temporal dependencies in vehicle operation. This combination enabled accurate prediction of future energy demand and optimized power distribution. The results demonstrated improved fuel efficiency and reduced emissions compared to standalone models. However, the high computational complexity of the architecture limited its real-time implementation.

Reddy et al. (2023) introduced a multi-objective optimization-based energy management strategy using evolutionary algorithms. The approach simultaneously optimized fuel consumption, emissions, and battery degradation by generating Pareto-optimal solutions. This allowed flexible decision-making based on specific performance requirements. The results showed improved system efficiency and adaptability compared to single-objective methods. However, the computational cost associated with multi-objective optimization remained a significant limitation.

Sharma et al. (2020) proposed an adaptive rule-based energy management strategy enhanced with machine learning-based driving pattern recognition. The system classified driving conditions such as urban, highway, and mixed cycles using supervised learning techniques. Based on the identified driving mode, the EMS dynamically adjusted control rules for optimal energy distribution. The results showed improved fuel efficiency and reduced emissions compared to conventional rule-based approaches. The method was computationally efficient and suitable for real-time applications. However, it lacked global optimization capability and heavily depended on classification accuracy.

Zhou et al. (2020) introduced a stochastic model predictive control (MPC)-based energy management strategy integrated with probabilistic learning models. The approach considered uncertainties in driving conditions and traffic patterns, enabling more robust decision-making. By incorporating predictive information, the system improved fuel economy and reduced energy losses. Additionally, the method provided smoother transitions between engine and battery operations. However, the computational complexity of stochastic MPC and dependency on accurate probabilistic models limited its real-time applicability.

Huang et al. (2021) developed a policy gradient-based reinforcement learning approach for continuous control in PHEVs. Unlike value-based methods, this approach directly optimized control policies in continuous action spaces, making it suitable for complex energy management problems. The system demonstrated improved convergence stability and better fuel efficiency compared to traditional RL methods. Additionally, it effectively handled nonlinear system dynamics. However, the training process was computationally intensive and required extensive exploration, which increased training time. Yang et al. (2021) proposed a hierarchical energy management strategy combining optimization techniques with rule-based control. The upper layer utilized optimization algorithms to determine global energy allocation, while the lower layer executed real-time control decisions. This hybrid structure improved system flexibility and reduced computational burden. The results showed enhanced fuel efficiency and better battery utilization compared to single-layer approaches. However, coordination between layers introduced additional system complexity.

Sun et al. (2022) developed an attention-based graph neural network (GNN) framework for energy management in PHEVs. The model integrated attention mechanisms to identify and prioritize critical features influencing energy consumption. This improved the model's ability to capture both spatial and temporal dependencies among vehicle components. The results demonstrated enhanced energy efficiency and reduced emissions compared to traditional GCN-based models. However, the increased model complexity required high computational resources and large datasets for training. Verma et al. (2023) introduced a swarm intelligence-based energy management strategy inspired by natural behaviours such as flocking and collective movement. The approach explored multiple candidate solutions simultaneously, enabling efficient global optimization. The results showed faster convergence and improved fuel efficiency compared to traditional optimization methods. Additionally, the system effectively handled nonlinear constraints in complex driving conditions. However, the performance was sensitive to parameter selection and initial conditions.

Mehta et al. (2020) proposed an adaptive dynamic programming (ADP)-based energy management strategy for PHEVs. The approach used value function approximation to determine optimal control policies in real time. The system continuously updated its policy using feedback from the vehicle environment, enabling adaptability to changing driving conditions. Results showed improved fuel efficiency and reduced computational complexity compared to traditional dynamic programming. However, approximation errors affected the accuracy of the control strategy. Roy et al. (2021) introduced a hybrid fuzzy-neural network-based EMS that combined the interpretability of fuzzy logic with the learning capability of neural networks. The system effectively handled uncertainties in driving conditions and improved decision-making accuracy. Simulation results showed enhanced fuel efficiency and emission reduction. However, integrating fuzzy systems with neural

networks increased design complexity and required expert knowledge.
Das et al. (2021) developed an ant colony optimization (ACO)-based energy management strategy. The algorithm mimicked the foraging behaviour of ants to find optimal energy distribution paths. The approach demonstrated improved convergence speed and better solution quality compared to traditional optimization techniques. However, the computational cost increased significantly for large-scale problems, limiting real-time implementation. Iqbal et al. (2022) proposed a recurrent neural network (RNN)-based energy management strategy for predicting future energy demand in PHEVs. The model captured temporal dependencies in driving patterns, enabling more accurate energy allocation. Results showed improved prediction accuracy and fuel efficiency compared to conventional models. However, the model required large datasets and was prone to overfitting.
Choudhary et al. (2022) introduced a multi-objective genetic algorithm (MOGA)-based EMS that optimized fuel consumption, emissions, and battery degradation simultaneously. The approach generated Pareto-optimal solutions, providing flexibility in selecting optimal trade-offs. The results demonstrated improved system efficiency compared to single-objective methods. However, the high computational cost limited real-time applicability. Banerjee et al. (2023) proposed a convolutional neural network (CNN)-based energy management system for PHEVs. The model extracted relevant features from driving data and optimized control decisions accordingly. The approach showed improved performance and reduced computational overhead compared to deeper architectures. However, it required large training datasets to achieve optimal results.

**Comparative Table**

| Study | Year | AI Technique | Method | Key Contribution | Limitation |
|---|---|---|---|---|---|
| Zhang | 2020 | RL | DQN | Adaptive EMS | High training cost |
| Li | 2020 | AI + MPC | Predictive EMS | Better efficiency | Prediction dependency |
| Wang | 2021 | Hybrid AI | PSO + NN | Improved optimization | Complex tuning |
| Chen | 2021 | DL | DNN | Real-time EMS | Data dependency |
| Liu | 2022 | RL | TD3 | Stable control | High computation |
| Zhao | 2022 | GNN | GCN | Relational modelling | Complex training |
| Sun | 2022 | GNN | Attention GNN | Better accuracy | Resource intensive |
| Singh | 2023 | Hybrid AI | Fuzzy + ML | Interpretability | Scalability |
| Patel | 2023 | DL | CNN-LSTM | Temporal modelling | High complexity |
| Reddy | 2023 | Optimization | Multi-objective | Trade-offs | High computation |
| Sharma | 2020 | ML | Rule-based adaptive | Real-time EMS | Limited optimality |
| Zhou | 2020 | AI + MPC | Stochastic MPC | Robust control | High complexity |
| Huang | 2021 | RL | Policy gradient | Continuous control | Long training |
| Yang | 2021 | Hybrid | Hierarchical | Balanced approach | Complex design |
| Park | 2022 | RL | DDPG | Continuous control | Hyperparameter tuning |
| Verma | 2023 | Swarm AI | SI | Fast convergence | Sensitive parameters |
| Tan | 2023 | RL | Multi-agent | Scalability | Coordination issue |

| | | | | | |
|---|---|---|---|---|---|
| Mehta | 2020 | AI | ADP | Real-time EMS | Approximation error |
| Roy | 2021 | Hybrid AI | Fuzzy + NN | Adaptive EMS | Complexity |
| Das | 2021 | Optimization | ACO | Better solutions | High computation |
| Iqbal | 2022 | DL | RNN | Prediction | Overfitting |
| Choudhary | 2022 | Optimization | MOGA | Multi-objective | Slow |
| Banerjee | 2023 | DL | CNN | Efficient EMS | Data need |

**Comparative Analysis**

The comparative evaluation of AI-based energy management strategies for plug-in hybrid electric vehicles reveals a clear transition from conventional approaches toward intelligent, adaptive, and hybrid frameworks. Early methods such as rule-based and MPC-based strategies provided real-time feasibility but lacked adaptability and optimality in dynamic environments. The introduction of reinforcement learning techniques, including DQN, DDPG, and TD3, enabled adaptive decision-making and improved fuel efficiency by learning optimal policies directly from driving data. However, these methods require extensive training and computational resources. Deep learning models such as CNN, LSTM, and RNN enhanced predictive capabilities by capturing temporal and nonlinear relationships in vehicle data, but their complexity limits real-time deployment. Graph-based approaches, including GCN and GAT, further improved system performance by modelling relational dependencies among vehicle components.

The recent development of RBAGCN represents a significant advancement by incorporating hierarchical and relational aggregation, enabling more accurate and scalable EMS solutions. Additionally, bio-inspired algorithms such as Snow Geese Optimization provide efficient global search capabilities, overcoming local minima limitations of traditional optimization methods. Hybrid approaches that combine AI, optimization, and graph-based models demonstrate the best performance by balancing efficiency, adaptability, and scalability. Despite these advancements, challenges such as computational complexity, data dependency, and interpretability remain key research gaps.

**Discussion**

The integration of artificial intelligence techniques into energy management strategies for plug-in hybrid electric vehicles has significantly enhanced system performance, efficiency, and adaptability. Reinforcement learning and deep learning approaches have enabled EMS to dynamically adjust to changing driving conditions, leading to improved fuel economy and reduced emissions. Graph neural networks have further strengthened EMS capabilities by modelling complex relationships among vehicle subsystems, enabling more accurate and context-aware decision-making. Additionally, bio-inspired optimization algorithms such as Snow Geese Optimization provide robust global search capabilities, improving solution quality in multi-objective optimization problems. Despite these advancements, several challenges persist, including high computational requirements, large data dependency, and limited interpretability of AI models.

Real-time implementation remains a critical concern, especially for complex hybrid frameworks such as RBAGCN. Furthermore, the integration of multiple AI techniques increases system complexity, making design and optimization more challenging. Future research should focus on developing lightweight and efficient AI models that can operate in real-time environments. Enhancing model interpretability and reducing dependency on large datasets are also important areas for further investigation. The integration of emerging technologies such as connected vehicles and vehicle-to-grid systems offers additional opportunities for improving energy management strategies in next-generation PHEVs.

**Conclusion**

Artificial intelligence has become a key technology for developing efficient energy management strategies (EMS) in plug-in hybrid electric vehicles (PHEVs). This review examined recent AI-based EMS approaches, emphasizing their advantages, limitations, and practical significance. Conventional methods, including rule-based control and model predictive control, provide reliable operation but often struggle to adapt to changing driving conditions. In contrast, reinforcement learning algorithms such as DQN, DDPG, and TD3 enable adaptive decision-making without requiring detailed mathematical models, leading to improved fuel economy and battery utilization. Deep learning techniques, including CNNs and LSTMs, further enhance prediction accuracy and support intelligent energy allocation under dynamic operating environments.

Graph-based learning methods, particularly Graph Convolutional Networks (GCNs) and Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCNs), improve the modelling of interactions among vehicle components, resulting in more accurate and scalable EMS solutions. Snow Geese Optimization (SGO) complements these models by providing efficient global optimization for balancing fuel consumption, battery health, and emissions. The integration of SGO with graph-based deep learning forms a powerful hybrid framework for intelligent vehicle energy management.

Despite notable progress, challenges such as computational complexity, real-time deployment, and model interpretability remain. Future research should focus on lightweight, explainable, and scalable AI frameworks integrated with connected vehicles, edge computing, and vehicle-to-grid technologies. Overall, the combination of Snow Geese Optimization and RBAGCN offers a promising direction for developing intelligent, efficient, and sustainable next-generation PHEV energy management systems.

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