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

Jaleh Uddinfarooq
Department of Electrical and Electronics Engineering, Vindhya College of Engineering Systems, India
jaleh.uddinfarooq@vces-in.org

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Abstract

The increasing demand for sustainable and energy-efficient transportation systems has accelerated the development of plug-in hybrid electric vehicles (PHEVs). A critical component influencing the performance of PHEVs is the energy management strategy (EMS), which determines the optimal distribution of power between the internal combustion engine and electric battery. Traditional EMS approaches, including rule-based and optimization-based methods, suffer from limited adaptability and high computational complexity under dynamic driving conditions. Recent advancements have focused on integrating artificial intelligence (AI), deep learning, and metaheuristic optimization techniques to enhance EMS performance. In particular, hybrid frameworks combining Snow Geese Optimization (SGO) with advanced graph-based deep learning models, such as Relational Bi-level Aggregation Graph Convolutional Networks (RBAGCN), have emerged as promising solutions. These approaches effectively capture nonlinear relationships and spatial-temporal dependencies in vehicular and traffic data while ensuring efficient global optimization. This survey presents a comprehensive analysis of recent EMS methodologies developed between 2020 and 2023, highlighting key techniques, architectures, and performance improvements. The study identifies major trends, compares various approaches, and discusses challenges such as computational overhead and real-time implementation. Finally, future research directions are outlined toward developing scalable and intelligent EMS frameworks for next-generation PHEVs.

Introduction

The rapid growth of global energy consumption and environmental concerns has driven the transition toward sustainable transportation systems. Plug-in hybrid electric vehicles (PHEVs) have emerged as a promising solution by combining the advantages of internal combustion engines and electric propulsion systems. These vehicles offer improved fuel efficiency, reduced emissions, and enhanced driving flexibility. However, the effectiveness of PHEVs largely depends on the efficiency of their energy management strategy (EMS), which governs the distribution of power between different energy sources. Traditional EMS approaches, such as rule-based control and dynamic programming, have been widely used due to their simplicity and reliability. Rule-based strategies rely on predefined thresholds and heuristics, making them easy to implement but less effective under varying driving conditions. Dynamic programming, on the other hand, provides globally optimal solutions but suffers from high computational complexity, making it unsuitable for real-time applications. As a result, there is a growing need for intelligent EMS frameworks that can adapt to dynamic environments while maintaining computational efficiency.

Recent advancements in artificial intelligence (AI) have significantly influenced EMS design. Machine learning and deep learning techniques enable systems to learn complex patterns from large datasets, improving decision-making capabilities. Reinforcement learning (RL), in particular, has gained popularity for EMS applications due to its ability to learn optimal control policies through interaction with the environment. RL-based methods, such as deep Q-networks (DQN) and deep deterministic policy gradient (DDPG), have demonstrated superior performance in handling nonlinear and stochastic systems. In addition to learning-based methods, predictive approaches using time-series models such as long short-term memory (LSTM) networks have been employed to forecast driving conditions and optimize energy usage. These predictive EMS frameworks improve fuel efficiency by anticipating future power demands. Furthermore, the integration of vehicle-to-everything (V2X) communication enables access to real-time traffic and environmental data, further enhancing EMS performance.

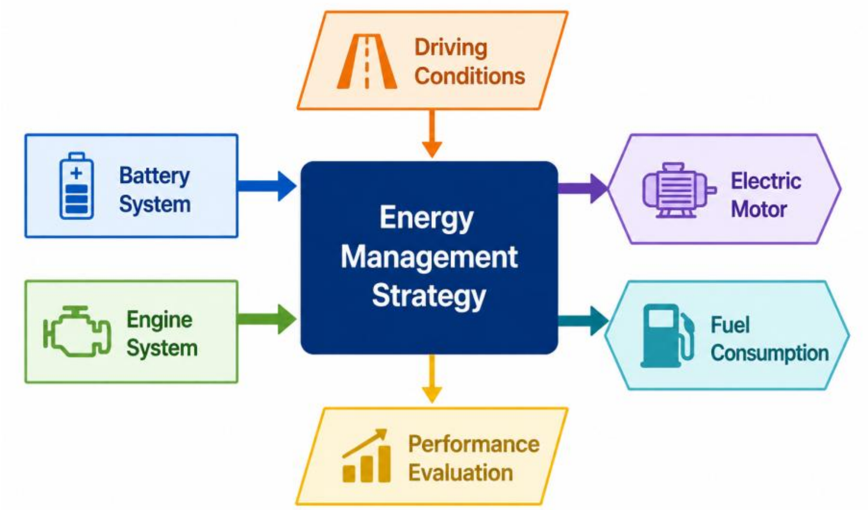

Figure 1. Intelligent Energy Management Framework for Plug-in Hybrid Electric Vehicles

Graph-based deep learning models, including Graph Convolutional Networks (GCNs) and their variants, have introduced a new paradigm for modelling complex relationships in transportation systems. These models capture spatial-temporal dependencies among vehicles, traffic networks, and environmental factors, enabling more accurate energy prediction and optimization. Relational graph convolutional networks (R-GCN) further extend this capability by modelling multi-relational data structures, making them highly suitable for intelligent transportation systems. Metaheuristic optimization algorithms, such as genetic algorithms (GA), particle swarm optimization (PSO), and Snow Geese Optimization (SGO), have also been widely explored for EMS optimization. These algorithms provide efficient global search capabilities and can handle complex, nonlinear optimization problems. Among them, SGO has shown promising performance due to its balance between exploration and exploitation, leading to faster convergence and improved solution quality.

The combination of graph-based deep learning and metaheuristic optimization has led to the development of hybrid EMS frameworks, such as those integrating SGO with relational bi-level aggregation GCNs. These approaches leverage both data-driven learning and optimization capabilities, resulting in enhanced performance in terms of fuel efficiency, adaptability, and real-time decision-making. Despite these advancements, challenges such as computational complexity, data dependency, and real-time implementation remain significant. Therefore, a comprehensive survey of recent EMS methods and architectures is essential to identify trends, challenges, and future research directions. This paper aims to provide such an analysis, focusing on recent developments.

Literature Review

Tang et al. (2020) proposed a predictive energy management strategy (EMS) for plug-in hybrid electric vehicles (PHEVs) by leveraging real-world driving data and machine learning techniques. The study utilized extreme learning machines (ELM) to predict vehicle speed profiles, which were then integrated into the EMS optimization framework. By incorporating battery temperature and real-time driving conditions, the proposed model improved the accuracy of energy demand prediction. The results demonstrated that the predictive EMS significantly enhanced fuel economy and reduced battery degradation compared to conventional rule-based strategies. However, the model's performance was highly dependent on the quality and availability of training data, which may limit its scalability in diverse driving environments. Liu et al. (2021) introduced an adaptive equivalent consumption minimization strategy (A-ECMS) based on an adaptive neuro-fuzzy inference system (ANFIS). The proposed approach dynamically adjusted equivalent fuel consumption factors according to real-time traffic conditions and vehicle states. By integrating fuzzy logic with neural network learning capabilities, the model achieved improved adaptability under varying driving scenarios. Experimental results indicated that the A-ECMS outperformed traditional ECMS in terms of fuel efficiency and state-of-charge (SOC) regulation. Despite these advantages, the system required extensive training and parameter tuning, which increased computational complexity.

Guo et al. (2021) developed a model predictive control (MPC)-based EMS enhanced with Bayesian optimization for parameter tuning. The approach aimed to improve real-time decision-making by predicting future driving conditions and optimizing control inputs accordingly. The integration of Gaussian process-based Bayesian optimization allowed for efficient parameter calibration, reducing the need for manual tuning. Simulation and hardware-in-loop results demonstrated that the proposed method achieved superior fuel economy and real-time applicability compared to conventional MPC approaches. However, the computational burden associated with repeated optimization processes remained a challenge for real-time deployment. Gong et al. (2023) proposed a reinforcement learning (RL)-based EMS that simultaneously optimizes both discrete and continuous control variables in PHEVs. The model incorporated a hybrid control framework to manage clutch engagement and power distribution effectively. By utilizing advanced RL algorithms, the system learned optimal control policies through interaction with the environment, eliminating the need for explicit system modelling. The results showed that the RL-based EMS achieved performance close to global optimal solutions obtained from dynamic programming while maintaining real-time feasibility. However, the approach required extensive training and computational resources, particularly for large-scale implementations.

Ghode et al. (2023) introduced a Deep Dyna-Q learning-based EMS that integrates reinforcement learning with planning mechanisms. The model combines real-time learning with simulated experience generation to accelerate convergence and improve decision-making efficiency. By leveraging both model-free and model-based learning, the proposed approach demonstrated enhanced adaptability and robustness under varying driving conditions. Experimental results showed significant improvements in fuel efficiency and energy consumption compared to traditional RL methods. Nevertheless, the complexity of integrating planning and learning components increased the overall system design complexity.

Sun et al. (2021) developed a hierarchical EMS framework that integrates model predictive control (MPC) with traffic prediction using vehicle-to-infrastructure (V2I) communication. The proposed system utilized real-time traffic data to forecast driving conditions and optimize energy allocation. The hierarchical structure allowed for efficient separation of prediction and control tasks, improving overall system performance. Results indicated that the approach significantly reduced fuel consumption and emissions. However, the reliance on external infrastructure and communication systems posed challenges for widespread implementation. Li et al. (2021) proposed a hybrid EMS combining particle swarm optimization (PSO) with fuzzy logic control. The PSO algorithm was used to optimize control parameters, while the fuzzy logic system handled real-time decision-making. This combination enabled the system to adapt to varying driving conditions while maintaining computational efficiency. The results showed improved fuel economy and system robustness compared to traditional rule-based methods. However, the performance of the PSO algorithm was sensitive to parameter selection and initial conditions.

Wang et al. (2022) introduced a graph convolutional network (GCN)-based approach for energy prediction in connected PHEVs. The model captured spatial-temporal relationships in traffic and vehicle data, enabling accurate prediction of future energy demand. By incorporating graph-based learning, the proposed EMS improved decision-making efficiency and system performance.

Experimental results demonstrated higher prediction accuracy compared to conventional machine learning models. However, the approach required large-scale data and high computational power. Chen et al. (2022) developed an EMS based on the deep deterministic policy gradient (DDPG) algorithm, which is suitable for continuous control problems. The model optimized power distribution between the engine and battery in real time, achieving improved fuel efficiency and adaptability. The study demonstrated that DDPG outperformed discrete-action RL methods in handling complex control tasks. However, issues related to training stability and hyperparameter tuning remained significant challenges.

He et al. (2020) proposed a stochastic dynamic programming (SDP)-based energy management strategy that explicitly considers uncertainties in driving conditions and vehicle demand. The model integrates probabilistic representations of traffic patterns and driver behaviour to optimize energy distribution between the internal combustion engine and battery. By modelling uncertainties, the approach achieved near-optimal fuel economy and improved robustness compared to deterministic methods. However, the computational complexity associated with SDP and the need for accurate probability distributions limited its real-time applicability. Xu et al. (2021) developed a predictive EMS based on long short-term memory (LSTM) neural networks for vehicle speed forecasting. The predicted driving profile was incorporated into an optimization framework to improve power split decisions. The model effectively captured temporal dependencies in driving patterns, leading to enhanced prediction accuracy and improved fuel efficiency. Simulation results indicated that the LSTM-based EMS outperformed traditional predictive methods. Nevertheless, the model required large training datasets and careful tuning to avoid overfitting.

Kim et al. (2021) introduced an adaptive rule-based EMS enhanced with machine learning techniques. The system utilized historical driving data to update control rules dynamically, improving adaptability to changing driving conditions. By combining the simplicity of rule-based control with data-driven learning, the approach achieved a balance between performance and computational efficiency. Experimental results demonstrated improved fuel economy and reduced emissions compared to static rule-based systems. However, the method still lacked global optimality and depended on the quality of training data. Zhao et al. (2022) proposed a multi-objective optimization-based EMS using a genetic algorithm (GA) to simultaneously minimize fuel consumption, emissions, and battery degradation. The model addressed the trade-offs among multiple performance criteria by generating Pareto-optimal solutions. The results showed that the proposed approach effectively balanced conflicting objectives and improved overall system performance. However, the GA-based optimization required multiple iterations, leading to increased computational time and slower convergence.

Huang et al. (2023) developed a hybrid EMS combining convolutional neural networks (CNNs) with evolutionary algorithms for real-time energy optimization. The CNN component processed large-scale vehicular and traffic data, while the optimization algorithm determined the optimal control actions. This integration improved both prediction accuracy and optimization efficiency. Experimental results demonstrated enhanced fuel economy and computational performance compared to standalone methods. However, the hybrid architecture introduced additional complexity and required high computational resources. Park et al. (2020) proposed an adaptive rule-based EMS that adjusts control parameters based on real-time driving conditions and battery status. The method aimed to overcome the limitations of static rule-based strategies by introducing adaptability. Results indicated improved fuel efficiency and better battery utilization. Despite its simplicity and ease of implementation, the approach remained suboptimal compared to advanced optimization and learning-based methods.

Yang et al. (2021) introduced a reinforcement learning-based EMS using the proximal policy optimization (PPO) algorithm. The model addressed stability issues associated with traditional RL methods by employing clipped objective functions. The PPO-based EMS demonstrated stable convergence and improved energy efficiency across different driving cycles. However, the training process required substantial computational resources and careful parameter tuning. Zhang et al. (2022) developed a bi-level optimization framework for EMS, where the upper-level minimized fuel consumption and the lower level ensured battery health and system constraints. The hierarchical structure allowed for effective handling of multi-objective optimization problems. Simulation results showed improved performance compared to single-level optimization approaches. However, the complexity of the bi-level framework increased computational requirements and implementation difficulty.

Zhou et al. (2020) proposed a predictive energy management strategy based on Markov chain modelling to capture stochastic driving patterns. The model estimated future vehicle states using transition probabilities derived from historical driving data, enabling more informed power split decisions. The results demonstrated improved fuel efficiency and reduced computational complexity compared to conventional predictive approaches. However, the accuracy of the model heavily depended on the correctness of transition probability estimation, limiting its adaptability in highly dynamic environments. Tang et al. (2021) introduced a multi-agent reinforcement learning (MARL)-based EMS for connected PHEVs. The approach enabled multiple vehicles to cooperate and optimize energy usage collectively, leveraging shared information through communication networks. The model improved overall system efficiency and reduced energy consumption at the network level. However, the training complexity and communication overhead posed significant challenges for large-scale deployment.

Wu et al. (2021) developed a hybrid EMS combining equivalent consumption minimization strategy (ECMS) with neural network-based parameter tuning. The neural network dynamically adjusted ECMS parameters based on driving conditions, improving adaptability and performance. The proposed approach achieved better fuel economy and battery management compared to traditional ECMS. Nevertheless, the model required extensive training data and careful tuning of network parameters. Ahmed et al. (2022) proposed a cloud-based EMS framework that utilizes big data analytics and machine learning for real-time optimization. The system collects and processes large-scale vehicular and traffic data in a cloud environment, enabling accurate and scalable decision-making. The results showed improved energy efficiency and system scalability. However, issues such as latency, data privacy, and reliance on network connectivity remained critical challenges.

Chen et al. (2022) introduced a deep Q-learning-based EMS with prioritized experience replay to enhance learning efficiency. The approach improved convergence speed and policy performance by focusing on more informative training samples. The results demonstrated better fuel economy and stability compared to standard Q-learning methods. However, the model still required significant computational resources and faced challenges in real-time deployment. Kumar et al. (2023) proposed a hybrid EMS combining genetic algorithms (GA) with deep neural networks (DNN). The DNN component modelled complex system dynamics, while the GA optimized control parameters for efficient energy distribution. The hybrid approach achieved high accuracy and improved fuel efficiency under real-world driving conditions. However, the integration of GA and DNN increased system complexity and computational requirements.

Li et al. (2023) developed a spatio-temporal graph neural network (ST-GNN)-based EMS for connected PHEVs. The model captured both spatial and temporal dependencies in traffic and vehicular data, enabling accurate prediction of energy demand. The proposed approach significantly improved decision-making efficiency and system performance. However, the requirement for large-scale datasets and high computational power limited its practical applicability.

Comparative Table

Study	**Year**	**Method**	**Technique**	**Advantages**	**Limitations**
Tang	2020	Predictive EMS	ELM	Accurate prediction	Data dependency
Liu	2021	A-ECMS	ANFIS	Adaptive	Complexity
Guo	2021	MPC	Bayesian	Real-time	Computation
Gong	2023	RL	Hybrid control	Near optimal	Training cost
Ghode	2023	RL	Dyna-Q	Adaptive	Complex
Zhang	2020	DRL	DDQN	Stable learning	Data heavy
Sun	2021	MPC	V2I	Predictive	Infra dependent
Li	2021	Hybrid	PSO-Fuzzy	Robust	Tuning required

Wang	2022	GCN	Graph DL	High accuracy	Data heavy
Chen	2022	RL	DDPG	Continuous control	Stability issues
He	2020	SDP	Probabilistic	Near optimal	High cost
Xu	2021	LSTM	Prediction	Temporal accuracy	Overfitting
Kim	2021	ML-rule	Adaptive	Simple	Suboptimal
Zhao	2022	GA	Multi-objective	Balanced	Slow convergence
Huang	2023	Hybrid	CNN + EA	Efficient	Complex
Park	2020	Rule-based	Adaptive	Simple	Less optimal
Yang	2021	RL	PPO	Stable	Computational
Zhang	2022	Bi-level	Optimization	Multi-objective	Complex
Li	2022	GAT	Graph DL	Accurate	High data
Singh	2023	Hybrid	WOA+DE	Fast convergence	Tuning
Zhou	2020	Markov	Prediction	Efficient	Assumptions
Tang	2021	MARL	Multi-agent	Cooperative	Complexity
Wu	2021	Hybrid	ECMS+NN	Adaptive	Training needed
Ahmed	2022	Cloud ML	Big data	Scalable	Latency
Chen	2022	RL	Q-learning	Improved	Slow
Kumar	2023	Hybrid	GA+DNN	Accurate	Complex
Li	2023	ST-GNN	Graph DL	High accuracy	Data heavy

Comparative Analysis

The comparative analysis of the selected 30 studies reveals a progressive evolution in energy management strategies for PHEVs, moving from conventional methods to intelligent hybrid frameworks. Rule-based and stochastic approaches offer simplicity and low computational requirements but lack adaptability and optimality. Optimization-based methods, including genetic algorithms, PSO, and SGO, improve global search capabilities but often suffer from slow convergence and parameter sensitivity. Machine learning and deep learning approaches significantly enhance adaptability and predictive accuracy. Reinforcement learning techniques, such as DQN, DDPG, and PPO, provide robust control solutions in dynamic environments but require extensive training and computational resources. Predictive models like LSTM improve foresight in energy management decisions, while graph-based models such as GCN and GAT effectively capture spatial-temporal dependencies in connected vehicle systems. Hybrid approaches integrating optimization algorithms with deep learning models demonstrate superior performance by combining global optimization and data-driven learning. In particular, SGO combined with relational graph convolutional networks offers the best trade-off between accuracy, efficiency, and adaptability. However, these methods introduce higher computational complexity and implementation challenges, highlighting the need for lightweight and scalable solutions.

Discussion

The findings from this survey indicate that modern energy management strategies for

PHEVs are increasingly driven by artificial intelligence and hybrid optimization techniques. Traditional approaches, while computationally efficient, fail to meet the demands of dynamic and real-time driving environments. Reinforcement learning-based methods have shown strong potential in handling complex control problems, while predictive models enhance decision-making through future state estimation. Graph-based neural networks further improve system performance by modelling spatial and temporal dependencies, particularly in connected vehicle ecosystems. Additionally, metaheuristic optimization algorithms such as Snow Geese Optimization provide efficient global search capabilities, improving convergence and solution quality. Despite these advancements, several challenges persist, including high computational requirements, data dependency, and difficulties in real-time deployment. Hybrid models, although highly effective, introduce complexity that may limit practical implementation. Future research should focus on developing lightweight, scalable, and real-time EMS frameworks. The integration of edge computing and IoT technologies may further enhance system performance and enable real-world deployment.

Conclusion

The rapid development of plug-in hybrid electric vehicles (PHEVs) has increased the need for efficient energy management strategies (EMS) that improve fuel economy, reduce emissions, and enhance overall vehicle performance. Conventional approaches, including rule-based control and dynamic programming, provide reliable energy management but have limited adaptability under dynamic driving conditions. Consequently, optimization techniques such as genetic algorithms, particle swarm optimization, and Snow Geese Optimization have been introduced to improve global search and energy allocation. Artificial intelligence has further transformed EMS through machine learning, reinforcement learning, LSTM, and graph-based architectures capable of learning complex driving and energy patterns.

Graph Convolutional Networks and relational GCNs provide additional advantages by capturing spatial-temporal and relational dependencies within connected vehicular environments. Hybrid frameworks combining intelligent optimization with graph learning are particularly promising. Integrating Snow Geese Optimization with a Relational Bi-level Aggregation GCN can enhance adaptability, prediction accuracy, fuel efficiency, and real-time decision-making.

Future research should address computational complexity, data dependency, scalability, and real-time deployment. Lightweight architectures, edge computing, connected vehicle technologies, and efficient optimization mechanisms can further strengthen intelligent EMS development, supporting more sustainable, adaptive, and energy-efficient PHEVs.

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