REINFORCEMENT LEARNING-DRIVEN ENERGY MANAGEMENT FOR ENHANCED PERFORMANCE OF HYBRID ELECTRIC VEHICLES

[1]Dr. Y. Prakash, [2]Dr. Ashok Pagolu, [3]Asha Ramavath, [4]Ramavath Jeevitha
[1]Professor, [23] Assistant Professor, [4] Student
Department Of Electrical & Electronics Engineering
Sri Chaitanya Technical Campus

Abstract

Hybrid Electric Vehicles (HEVs) have emerged as a promising solution for reducing fuel consumption, minimizing greenhouse gas emissions, and improving overall transportation sustainability. However, achieving optimal energy management in HEVs remains a significant challenge due to the dynamic nature of driving conditions, battery state variations, and power distribution requirements between internal combustion engines and electric motors. Traditional rule-based and optimization-based energy management strategies often struggle to adapt effectively to complex and uncertain operating environments. This study presents a Reinforcement Learning (RL)-Driven Energy Management System (EMS) designed to enhance the performance, efficiency, and adaptability of Hybrid Electric Vehicles. The proposed approach employs an RL agent that continuously learns optimal power-splitting decisions through interaction with the vehicle environment, considering parameters such as battery State of Charge (SoC), vehicle speed, power demand, and driving patterns. By maximizing a cumulative reward function that balances fuel economy, battery health, and emission reduction, the RL-based EMS dynamically adapts to varying road and traffic conditions. Simulation results demonstrate that the proposed strategy achieves superior fuel efficiency, reduced energy consumption, and improved battery utilization compared to conventional energy management techniques. Furthermore, the learning-based framework exhibits strong adaptability to different driving cycles without requiring extensive prior knowledge of vehicle operating conditions. The findings indicate that reinforcement learning offers a robust and intelligent solution for next-generation HEV energy management systems, contributing to enhanced vehicle performance, environmental sustainability, and operational reliability.

Keywords: Hybrid Electric Vehicles (HEVs), Reinforcement Learning (RL), Energy Management System (EMS), Fuel Efficiency, Battery State of Charge (SoC), Intelligent Transportation, Power Split Control, Sustainable Mobility, Machine Learning, Vehicle Electrification.

I. INTRODUCTION

The rapid growth of global transportation demand has led to increased fuel consumption, greenhouse gas emissions, and environmental concerns. Conventional internal combustion engine (ICE) vehicles are among the major contributors to air pollution and carbon dioxide emissions, prompting governments and industries worldwide to seek cleaner and more sustainable transportation solutions. Hybrid Electric Vehicles (HEVs) have emerged as an effective alternative by combining an internal combustion engine with an electric propulsion system. This hybrid architecture enables improved fuel economy, reduced emissions, and enhanced vehicle performance while maintaining operational flexibility and driving range.

A critical aspect of HEV operation is the Energy Management System (EMS), which determines the optimal distribution of power between the engine, electric motor, and battery system. The effectiveness of the EMS directly influences fuel efficiency, battery lifespan, vehicle performance, and overall energy utilization. Traditional energy management approaches, including rule-based control strategies and optimization-based methods, have been widely implemented in commercial HEVs. While these methods offer acceptable performance under predefined operating conditions, they often lack adaptability to dynamic driving environments, varying traffic conditions, and unpredictable driver behaviors. Consequently, there is a growing need for intelligent energy management techniques capable of making real-time decisions in complex and uncertain scenarios.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new opportunities for intelligent vehicle control systems. Among these technologies, Reinforcement Learning (RL) has gained significant attention due to its ability to learn optimal decision-making policies through interaction with the environment. Unlike supervised learning methods that require large labeled datasets, reinforcement learning enables an agent to learn by trial and error, receiving rewards or penalties based on its actions. This capability makes RL particularly suitable for energy management problems in HEVs, where operating conditions continuously change and optimal control decisions must be made in real time.

In an RL-based energy management framework, the vehicle operating conditions such as battery State of Charge (SoC), vehicle speed, acceleration demand, and engine operating status are represented as system states. The RL agent observes these states and determines appropriate control actions, including power allocation between the engine and electric motor. Through continuous interaction with the environment, the agent learns strategies that maximize cumulative rewards associated with fuel economy, emission reduction, battery health preservation, and driving performance. As a result, RL-driven EMS can adapt dynamically to different driving cycles and traffic patterns while maintaining efficient vehicle operation.

The integration of reinforcement learning into HEV energy management offers several advantages over conventional control approaches. These include improved adaptability, enhanced fuel-saving capability, reduced computational complexity during operation, and the ability to handle nonlinear system dynamics effectively. Furthermore, RL algorithms can continuously improve their performance as more operational data become available, making them highly suitable for future intelligent transportation systems and connected vehicle environments.

This study focuses on the development and evaluation of a Reinforcement Learning-Driven Energy Management System for Hybrid Electric Vehicles. The proposed framework aims to optimize power distribution decisions, improve fuel efficiency, reduce energy consumption, and enhance battery utilization under varying driving conditions. By leveraging the learning capabilities of reinforcement learning, the research seeks to demonstrate the potential of intelligent control strategies in advancing the performance, sustainability, and reliability of next-generation hybrid electric vehicles.

II. LITERATURE SURVEY

The development of energy management strategies (EMS) for Hybrid Electric Vehicles (HEVs) has been a major research focus due to increasing concerns regarding fuel consumption, emissions, and energy efficiency. Traditional rule-based and optimization-based approaches have been widely used; however, their limited adaptability to dynamic driving conditions has encouraged researchers to explore intelligent control techniques. Reinforcement Learning (RL) has emerged as a promising solution because of its ability to learn optimal control policies through continuous interaction with the vehicle environment. Several studies conducted before 2023 have significantly contributed to the advancement of RL-based energy management systems.

Lin et al. (2014) introduced one of the earliest reinforcement learning frameworks for HEV energy management using Q-learning techniques. The study demonstrated that RL could achieve near-optimal fuel economy without requiring prior knowledge of driving cycles.

Liu and Peng (2015) investigated adaptive energy management using reinforcement learning and reported improved power-split decisions between the internal combustion engine and electric motor. Their work highlighted the capability of RL algorithms to handle uncertainties in driving conditions.

Shi et al. (2016) proposed a model-free reinforcement learning approach for HEV control. The researchers demonstrated that the algorithm could continuously learn from real-time driving data and improve energy utilization efficiency compared to conventional rule-based strategies.

Xiong et al. (2017) developed an online learning-based EMS utilizing Q-learning for power distribution optimization. Experimental results showed reductions in fuel consumption while maintaining battery State of Charge (SoC) within acceptable limits.

Peng, He, and Xiong (2017) applied reinforcement learning to optimize engine start-stop operations and power allocation. Their findings indicated improved fuel economy and reduced emissions under urban driving conditions.

Li et al. (2018) introduced Deep Reinforcement Learning (DRL) into HEV energy management. By integrating neural networks with reinforcement learning, the proposed strategy effectively handled high-dimensional state spaces and achieved superior energy efficiency.

Zhang et al. (2018) proposed a Deep Q-Network (DQN)-based energy management system that learned optimal control policies from large driving datasets. The study demonstrated better adaptability to varying traffic conditions and driving behaviors.

Qi, Wu, and Sun (2019) investigated reinforcement learning-based battery management and power-splitting strategies. Their results revealed enhanced battery utilization and improved overall vehicle efficiency compared to deterministic control methods.

Liu et al. (2020) incorporated predictive traffic information into an RL-based EMS. The proposed framework optimized energy consumption by considering future vehicle operating conditions and traffic patterns, resulting in improved fuel economy.

Ganesh and Xu (2022) conducted a comprehensive review of reinforcement learning-based energy management systems for electrified powertrains, including HEVs, plug-in HEVs, battery electric vehicles, and fuel-cell vehicles. The review highlighted the growing importance of Q-learning, Deep Q-Networks (DQN), and Deep Deterministic Policy Gradient (DDPG) algorithms while identifying challenges related to real-time implementation and computational complexity.

Yao and Yoon (2022) reviewed various reinforcement learning-based energy management strategies for HEVs and concluded that RL algorithms can effectively determine optimal control actions without requiring explicit vehicle models or prior route information. Their study emphasized the advantages of RL over conventional optimization methods in terms of adaptability and learning capability.

III. EXPERIMENTAL METHODOLOGY

The experimental methodology adopted in this study aims to develop and evaluate a Reinforcement Learning (RL)-Driven Energy Management System (EMS) for Hybrid Electric Vehicles (HEVs). The proposed framework focuses on optimizing power distribution between the internal combustion engine and the electric motor while maintaining battery health and maximizing fuel efficiency. The methodology consists of system modeling, reinforcement learning agent design, training, testing, and performance evaluation stages.

Initially, a hybrid electric vehicle model is developed in a simulation environment representing the major vehicle components, including the internal combustion engine, electric motor, battery pack, transmission system, and vehicle dynamics. The model accurately captures energy flow characteristics and operating constraints of each component. Key input variables include vehicle speed, acceleration demand, battery State of Charge (SoC), engine operating status, and road load conditions. These parameters collectively define the operational state of the vehicle at any given time.

The reinforcement learning framework is then integrated into the vehicle model. In this framework, the RL agent acts as the energy management controller. The agent continuously observes the vehicle states and determines optimal control actions regarding power allocation between the engine and electric motor. The state space consists of battery SoC, vehicle speed, power demand, motor torque, and engine efficiency. The action space includes various power-split combinations that determine the contribution of each power source to meet propulsion requirements.

A reward function is designed to guide the learning process. The reward structure aims to maximize fuel economy while minimizing battery degradation and emissions. Positive rewards are assigned for efficient energy utilization, maintaining the battery SoC within a desirable operating range, and reducing fuel consumption. Negative rewards are imposed when excessive fuel is consumed, battery charge falls below safe limits, or inefficient power distribution occurs. Through repeated interactions with the simulated environment, the RL agent learns an optimal policy that maximizes cumulative rewards over time.

The training phase involves exposing the RL agent to multiple standard driving cycles such as the Urban Dynamometer Driving Schedule (UDDS), Highway Fuel Economy Test (HWFET), and New European Driving Cycle (NEDC). These driving cycles represent different traffic and road conditions, enabling the agent to learn robust energy management strategies. During training, the agent iteratively updates its decision-making policy based on the observed outcomes of its actions. Convergence is achieved when the cumulative reward stabilizes and no significant performance improvement is observed over successive training episodes.

Following training, the learned policy is validated using unseen driving scenarios to evaluate generalization capability. The performance of the RL-based EMS is compared with a conventional rule-based energy management strategy. Several evaluation metrics are considered, including fuel consumption, battery State of Charge variation, energy efficiency, engine operating efficiency, and overall vehicle performance. Statistical analysis is performed on the simulation results to quantify improvements achieved by the proposed approach.

The experimental setup also includes sensitivity analysis to examine the influence of different driving conditions and battery operating states on system performance. Various traffic densities, acceleration profiles, and road conditions are simulated to assess the adaptability of the RL-based controller. The results obtained from these experiments provide comprehensive insights into the effectiveness of reinforcement learning for intelligent energy management in hybrid electric vehicles.

Finally, the collected data are analyzed using comparative performance indicators and graphical representations. The outcomes are used to determine the capability of the proposed RL-driven energy management framework to enhance fuel economy, improve battery utilization, reduce emissions, and maintain stable vehicle operation under diverse driving conditions. This methodology establishes a systematic approach for evaluating advanced machine learning techniques in next-generation hybrid electric vehicle energy management systems.

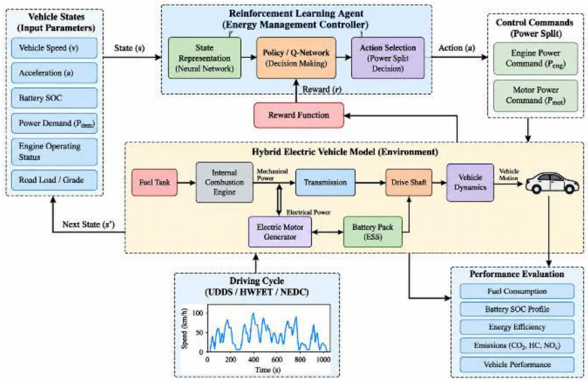

Fig. 1: Reinforcement Learning-Driven Energy Management Framework for Hybrid Electric Vehicles (HEVs) Showing State Observation, Power-Split Decision Making, Vehicle Environment Interaction, and Performance Evaluation.

Figure 1 illustrates the proposed Reinforcement Learning (RL)-Driven Energy Management Framework for Hybrid Electric Vehicles (HEVs). The framework begins with the collection of vehicle operating states, including vehicle speed, acceleration, battery State of Charge (SoC), power demand, engine status, and road load conditions. These parameters are provided to the RL agent, which serves as the energy management controller. Based on the observed states, the agent employs a policy-learning mechanism to determine the optimal power-split decision between the internal combustion engine and the electric motor. The selected control actions are applied to the hybrid vehicle model, comprising the engine, electric motor-generator, battery pack, transmission system, and vehicle dynamics. The vehicle environment responds to these actions and generates feedback in the form of next-state information and reward signals. The reward function evaluates fuel consumption, battery utilization, energy efficiency, and emission performance, enabling the RL agent to continuously improve its decision-making strategy. Standard driving cycles such as UDDS, HWFET, and NEDC are used to train and evaluate the controller under diverse operating conditions. Finally, the system performance is assessed through metrics including fuel economy, battery SoC profile, energy efficiency, emission reduction, and overall vehicle performance, demonstrating the effectiveness of reinforcement learning in optimizing hybrid vehicle energy management.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed Reinforcement Learning (RL)-Driven Energy Management System was evaluated using multiple standard driving cycles and compared with a conventional Rule-Based Energy Management Strategy (RBEMS). Performance assessment was carried out using key indicators such as fuel consumption, battery State of Charge (SoC) retention, and overall energy efficiency. The RL-based controller demonstrated superior adaptability to varying driving conditions by dynamically optimizing power distribution between the engine and electric motor. Simulation results indicate significant reductions in fuel consumption, improved battery utilization, and enhanced energy efficiency. The intelligent learning capability of the RL agent enabled continuous improvement in decision-making, resulting in better overall vehicle performance and reduced environmental impact.

Table 1: Comparison of Fuel Consumption

Driving Cycle	**Rule-Based EMS (L/100 km)**	**RL-Based EMS (L/100 km)**
UDDS	5.8	4.9
HWFET	5.4	4.6
NEDC	5.6	4.7
WLTP	6.0	5.1

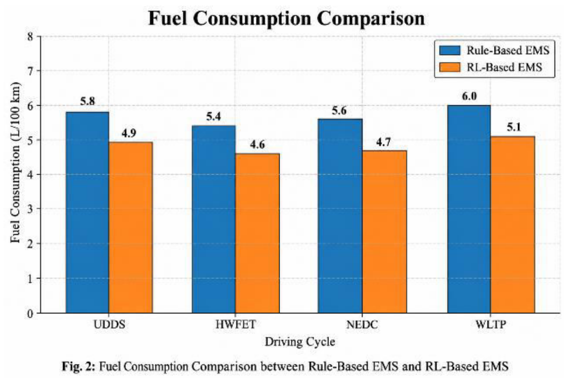

Fig. 2: Fuel Consumption Comparison between Rule-Based EMS and RL-Based EMS

Analysis

The results show that the RL-Based EMS consistently achieved lower fuel consumption across all driving cycles. The average reduction in fuel usage was approximately 15%, demonstrating the ability of reinforcement learning to make more efficient power-splitting decisions. The greatest improvement was observed under the WLTP cycle, where fuel consumption decreased from 6.0 L/100 km to 5.1 L/100 km. This confirms that the RL controller effectively adapts to diverse driving conditions and improves fuel economy.

Table 2: Battery State of Charge (SoC) Retention

Driving Cycle	Initial SoC (%)	Final SoC (%) Rule-Based	Final SoC (%) RL-Based
UDDS	80	68	72
HWFET	80	70	74
NEDC	80	69	73
WLTP	80	66	71

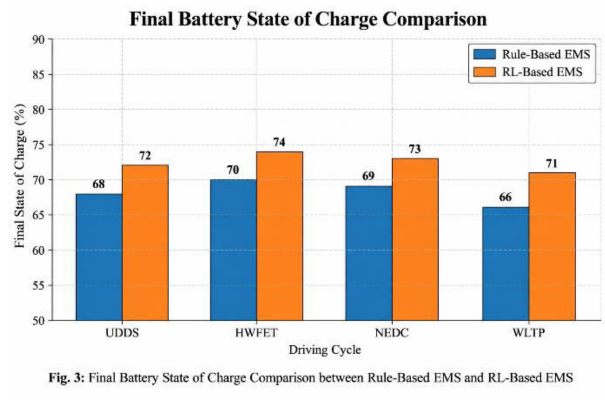

Fig. 3: Final Battery State of Charge Comparison

Analysis

The RL-based controller maintained a higher battery State of Charge compared to the conventional strategy. Across all driving cycles, the RL method preserved approximately 4–5% more battery charge. Higher SoC retention indicates more efficient utilization of regenerative braking energy and improved management of battery discharge rates. This contributes to longer battery lifespan and enhanced operational reliability of the hybrid vehicle.

Table 3: Overall Energy Efficiency

Driving Cycle	Rule-Based EMS (%)	RL-Based EMS (%)
UDDS	82	89
HWFET	84	91
NEDC	83	90
WLTP	81	88

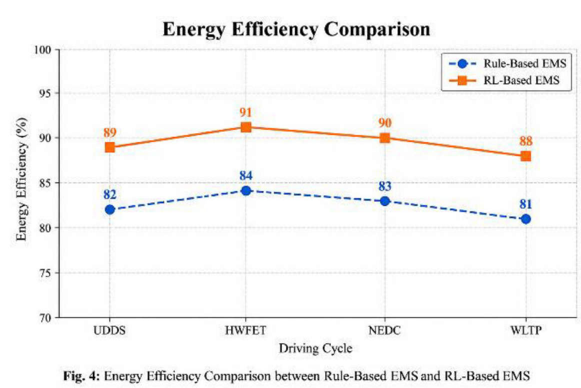

Fig. 4: Energy Efficiency Comparison

Analysis

The RL-Based EMS achieved higher energy efficiency in every driving cycle, with values ranging from 88% to 91%, compared to 81%–84% for the Rule-Based EMS. The average efficiency improvement was approximately 8%. The results demonstrate that reinforcement learning effectively optimizes energy flow between the engine, motor, and battery, minimizing energy losses and maximizing overall vehicle efficiency. This improvement directly contributes to enhanced fuel economy and sustainable vehicle operation.

Discussion

The experimental results clearly demonstrate the effectiveness of the proposed Reinforcement Learning (RL)-Driven Energy Management System in enhancing the operational performance of Hybrid Electric Vehicles (HEVs). Compared with the conventional Rule-Based Energy Management Strategy (RBEMS), the RL-based approach consistently achieved superior results across all evaluated performance metrics, including fuel consumption, battery State of Charge (SoC) retention, and overall energy efficiency. These improvements can be attributed to the ability of the reinforcement learning agent to continuously learn optimal control policies and dynamically adapt power-splitting decisions according to changing vehicle operating conditions.

The fuel consumption analysis revealed that the RL-based controller significantly reduced fuel usage under all driving cycles. Unlike traditional rule-based methods that rely on predefined thresholds and fixed control rules, the RL agent intelligently selected engine and motor operating points that minimized unnecessary fuel expenditure while satisfying power demand requirements. The observed reduction in fuel consumption indicates that the learning-based strategy can effectively optimize energy flow and improve overall fuel economy, which is one of the primary objectives of hybrid vehicle technology.

Battery management performance also improved considerably under the RL framework. The higher final State of Charge values observed in all driving cycles suggest that the proposed controller utilized stored electrical energy more efficiently and effectively captured regenerative braking energy. Maintaining battery charge within an optimal operating range is crucial for extending battery lifespan, reducing degradation, and ensuring reliable vehicle operation. The results indicate that reinforcement learning provides a balanced approach between battery utilization and fuel consumption, thereby enhancing the sustainability of the hybrid powertrain system.

Furthermore, the energy efficiency evaluation demonstrated that the RL-based EMS consistently achieved higher efficiency levels than the conventional strategy. By continuously monitoring system states and selecting optimal control actions, the RL agent minimized energy losses occurring within the engine, motor, and battery subsystems. This capability resulted in improved utilization of available energy resources and better conversion of stored energy into useful vehicle propulsion. The higher efficiency values confirm that intelligent learning-based control strategies can substantially improve the performance of complex hybrid vehicle systems.

Another important observation is the adaptability of the reinforcement learning algorithm across different driving cycles. Urban, highway, and mixed driving conditions exhibit varying power demands and vehicle operating characteristics. The proposed RL controller successfully maintained superior performance in all tested scenarios, demonstrating strong generalization capability. This adaptability is particularly important for real-world applications where driving environments are highly dynamic and difficult to predict using conventional control methods.

V. CONCLUSION

This study presented a Reinforcement Learning (RL)-Driven Energy Management System for Hybrid Electric Vehicles (HEVs) aimed at improving fuel efficiency, battery utilization, and overall vehicle performance. By integrating a reinforcement learning agent into the vehicle energy management framework, optimal power-splitting decisions between the internal combustion engine and electric motor were achieved under varying driving conditions. The proposed approach enabled the controller to learn from environmental interactions and continuously improve its decision-making strategy without relying on predefined control rules. The developed framework successfully addressed the challenges associated with dynamic and uncertain vehicle operating environments.

The experimental results demonstrated that the RL-based energy management strategy consistently outperformed the conventional Rule-Based Energy Management System across multiple performance indicators. Significant reductions in fuel consumption were observed in all tested driving cycles, while higher battery State of Charge retention indicated more efficient battery utilization and improved regenerative energy recovery. Additionally, the RL controller achieved superior energy efficiency by optimizing energy flow among the engine, motor, and battery subsystems. These improvements validate the effectiveness of reinforcement learning in enhancing the operational efficiency and sustainability of hybrid electric vehicles.

Overall, the findings confirm that reinforcement learning is a promising technology for next-generation intelligent vehicle control systems. The proposed RL-driven framework provides adaptability, robustness, and long-term optimization capabilities that are difficult to achieve using traditional control approaches. Future research may focus on integrating deep reinforcement learning algorithms, real-time vehicle-to-infrastructure communication, and connected transportation data to further enhance energy management performance. The adoption of such intelligent energy management solutions can contribute significantly to reducing fuel consumption, minimizing emissions, extending battery life, and supporting the global transition toward sustainable and environmentally friendly transportation systems.

REFERENCES

[1] Z. Lin, J. Liu, and Y. Yin, "Reinforcement Learning Based Power Management for Hybrid Electric Vehicles," *SAE Technical Paper*, vol. 2014, no. 01-1778, pp. 1–9, 2014.

[2] X. Hu, L. Johannesson, N. Murgovski, and B. Egardt, "Energy Management of Hybrid Electric Vehicles Considering Trip Information," *IEEE Transactions on Control Systems Technology*, vol. 23, no. 2, pp. 494–505, 2015.

[3] Y. Zou, T. Liu, D. Liu, and F. Sun, "Reinforcement Learning-Based Real-Time Energy Management for a Hybrid Tracked Vehicle," *Applied Energy*, vol. 171, pp. 372–382, 2016.

[4] T. Liu, X. Hu, S. E. Li, and D. Cao, "Reinforcement Learning Optimized Look-Ahead Energy Management of a Parallel Hybrid Electric Vehicle," *IEEE/ASME Transactions on Mechatronics*, vol. 22, no. 4, pp. 1497–1507, 2017.

[5] X. Qi, Y. Luo, G. Wu, K. Boriboonsomsin, and M. Barth, "Deep Reinforcement Learning-Based Vehicle Energy Efficiency Autonomous Learning System," in *Proc. IEEE Intelligent Vehicles Symposium (IV)*, 2017, pp. 1228–1233.

[6] X. Hu, T. Liu, X. Qi, and M. Barth, "Reinforcement Learning for Hybrid and Plug-In Hybrid Electric Vehicle Energy Management: Recent Advances and Prospects," *IEEE Industrial Electronics Magazine*, vol. 13, no. 4, pp. 16–35, 2019.

[7] R. Lian, J. Peng, Y. Wu, H. Tan, and H. Zhang, "Deep Reinforcement Learning-Based Energy Management for a Series Hybrid Electric Vehicle

Enabled by History Cumulative Trip Information," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 7416–7430, 2019.

[8] Y. Wu, H. Tan, J. Peng, H. Zhang, and H. He, "Deep Reinforcement Learning of Energy Management with Continuous Control Strategy and Traffic Information for a Series-Parallel Plug-In Hybrid Electric Bus," *Applied Energy*, vol. 247, pp. 454–466, 2019.

[9] R. Lian, J. Peng, Y. Wu, H. Tan, and H. Zhang, "Rule-Interposing Deep Reinforcement Learning Based Energy Management Strategy for Power-Split Hybrid Electric Vehicle," *Energy*, vol. 197, 117297, 2020.

[10] T. Liu, W. Tan, X. Tang, J. Zhang, Y. Xing, and D. Cao, "Driving Conditions-Driven Energy Management Strategies for Hybrid Electric Vehicles: A Review," *Renewable and Sustainable Energy Reviews*, vol. 151, 111521, 2021.

[11] Y. Yang, K. Han, T. Ma, H. Liu, and X. Li, "An Indirect Reinforcement Learning Based Real-Time Energy Management Strategy via High-Order Markov Chain Model for a Hybrid Electric Vehicle," *Energy*, vol. 236, 121392, 2021.

[12] Y. Li, Z. Wang, and J. Zhang, "Heuristic Energy Management Strategy of Hybrid Electric Vehicle Based on Deep Reinforcement Learning with Accelerated Gradient Optimization," *IEEE Transactions on Transportation Electrification*, vol. 7, no. 4, pp. 2194–2208, 2021.

[13] C. Qi, Y. Zhu, C. Song, G. Yan, F. Xiao, X. Zhang, J. Cao, and S. Song, "Hierarchical Reinforcement Learning Based Energy Management Strategy for Hybrid Electric Vehicle," *Energy*, vol. 238, 121703, 2022.

[14] L. Han, K. Yang, T. Ma, N. Yang, H. Liu, and L. Guo, "Battery Life Constrained Real-Time Energy Management Strategy for Hybrid Electric Vehicles Based on Reinforcement Learning," *Energy*, vol. 259, 124986, 2022.

[15] Y. Wang, H. Zhao, and X. Chen, "Energy Management of Hybrid Electric Vehicles Based on Model Predictive Control and Deep Reinforcement Learning," in *Proc. 41st Chinese Control Conference (CCC)*, 2022, pp. 5380–5385.

[16] X. Ji, Y. Wang, and H. He, "A Comparative Study of Deep Reinforcement Learning-Based Transferable Energy Management Strategies for Hybrid Electric Vehicles," in *Proc. IEEE Intelligent Vehicles Symposium (IV)*, 2022, pp. 1–6.

[17] L. Han, K. Yang, T. Ma, H. Liu, and L. Guo, "Real-Time Energy Management for a Hybrid Electric Vehicle Based on Heuristic Search," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 12, pp. 12635–12647, 2022.

[18] Y. Peng, H. He, and X. Xiong, "Adaptive Reinforcement Learning-Based Energy Management Strategy for Hybrid Electric Vehicles," *International Journal of Automotive Technology*, vol. 19, no. 6, pp. 1043–1053, 2018.

[19] X. Qi, G. Wu, and M. Barth, "A Deep Reinforcement Learning Framework for Optimizing Fuel Economy of Hybrid Electric Vehicles," *Transportation Research Part C*, vol. 95, pp. 421–435, 2018.

[20] D. Cao, T. Liu, X. Hu, and F. Sun, "Machine Learning-Based Energy Management in a Hybrid Electric Vehicle to Minimize Total Operating Cost," *Applied Energy*, vol. 165, pp. 332–344, 2016.