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SURVEY

A Comprehensive Review of Energy Management Strategies in Hybrid Electric Vehicles: Comparative Analysis and Challenges

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ABSTRACT As air pollution, greenhouse gases, and global warming worsen, finding clean energy sources is critical. Renewable energy is a promising solution, especially in the transportation sector, which consumes significant energy. Hybrid electric vehicles (HEVs), combining an internal combustion engine and an electric battery, are key to reducing fossil fuel use and mitigating environmental harm. Effectively managing power distribution between these sources to enhance efficiency and minimize fuel consumption is crucial, known as an Energy Management Strategy (EMS). This article provides an overview of various EMS approaches for HEVs, analyzing their advantages and disadvantages. Rule-based strategies offer simplicity, optimization-based strategies provide superior performance, and advanced techniques like machine learning promise significant improvements. Current trends include integrating sophisticated sensors, data analytics, and artificial intelligence for real-time decision-making. Future directions aim at robust EMS frameworks integrating smart grid technologies and vehicle-to-everything (V2X) communication. The article reviews EMS methodologies, comparing their strengths and weaknesses, and discusses the main challenges and future trends in energy management for hybrid electric vehicles.

INDEX TERMS Energy management strategies, hybrid electric vehicles, plug-in hybrid, offline and online control strategies, rule-based, optimization-based, deep learning, reinforcement learning.

I. INTRODUCTION

Several factors contribute to the alteration from standard vehicles to hybrid electric vehicles (HEVs). This segment delves into a comprehensive analysis of some of these factors, which have played a pivotal role in the advancement and growth of HEVs. Optimum utilization of energy in automobiles leads to the focus on the long-run availability of fossil fuels and environmental pollution. The average CO_2 emissions per capita in different countries from 2000 to 2025. The data can be summarized as,

1. The United States, Canada, and China have the highest CO_2 emissions per capita, while India, Japan, and the European Union have lower emissions.
2. All the countries shown have seen their CO_2 emissions per capita increase since 2000, except for the European Union, which has seen a slight decrease.
3. The United States has the highest overall CO_2 emissions per capita, followed by Canada and China.

It's important to note that these are just average CO_2 emissions per capita, and there is a lot of variation within each country. For example, in the United States, people who live in rural areas tend to have higher CO_2 emissions per capita than people who live in urban areas. There are several factors that contribute to CO_2 emissions, including the use of fossil fuels, deforestation, and industrial activity. There are a few things that can be done to reduce CO_2 emissions, such as using renewable energy sources, improving energy efficiency, and protecting forests. To reduce the loss of energy with increased

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efficiency within powertrain and internal combustion, promoting new technologies is required to meet the standard set out. Recently, the scientific community has done significant research to develop a few solutions, like increasing fuel efficiency with turbocharger removal of harmful gases using catalytic converters. With the rising traffic and ever-rising emission levels, a new technology was introduced which is likely to have:

1. Flexible performance with optimizing internal combustion engine.
2. Energy demand for performance of vehicle power source (42V-Electric, low lightening) energy systems.
3. Limit the loss due to rolling resistance, dynamic drag, and vehicle inertia's braking loss.

A. BASELINE VEHICLES AND THEIR LIMITATIONS

Standard vehicles equipped with internal combustion angles have a vast ground transport influence because of their extensive driving range and economical compared to other technologies [1]. The thermal efficiency of internal combustion engines surpasses that of spark ignition engines by 25% and compression ignition engines by 30%. Internal combustion engines primarily operate at their optimal efficiency due to the following factors:

1. Losses within the engine: The engine experiences two main types of losses, namely heat loss through the cylinder walls and limited compression ratios for fuel compression due to knock.
2. Very high random utilization of torque and speed of vehicle vary drastically on a continuous scale.
3. Effect of inertia.

These results in the adverse effects of fuel consumption and high emissions [2]. New technologies like HEVs can compensate for these negative effects and meet performance requirements. Leveraging hydroelectric power, modern trains now boast highly accessible propulsion systems. This feat is achieved through a hybrid powertrain comprising an electric battery, motor, and a combined electric-thermal drive coupler. By delivering on-demand power directly to the wheels, this system unlocks greater engine versatility, optimizing performance and adaptability.

The first hybrid electric vehicle was developed in 1899 by Dr. Ferdinand Porsche, where water-cooled combustion engines with 5 HP capacity were used to assist gasoline-powered engines. Due to the high cost associated with the development, this concept was short-lived. In 1995, this technology experienced a new attraction from manufacturers, which can result in emission reduction and optimum fuel utilization.

There are several key variations of HEVs depending on the type of electric motor, battery size, and powertrain configuration.

B. BY DEGREE OF HYBRIDIZATION

- Mild Hybrid (MHEV): These have small electric motors and batteries that assist the internal combustion engine (ICE) with tasks like starting the engine and providing additional power during acceleration. They cannot drive solely on electric power for significant distances [3].
- Full Hybrid (FHEV): These have larger electric motors and batteries that can propel the vehicle solely on electric power for short distances (typically 1-2 miles). They can also combine power from the electric motor and ICE for more efficient operation.
- Plug-in Hybrid (PHEV): These have larger batteries that can be charged from an external power source, allowing them to travel longer distances (typically 20-50 miles) solely on electric power. They function similarly to FHEVs when the battery is depleted.

C. BY POWERTRAIN CONFIGURATION

- Parallel Hybrid: Both the electric motor and ICE are connected to the wheels through the transmission, allowing for independent or combined operation. FHEVs and some PHEVs use this configuration.
- Serial Hybrid: The electric motor drives the wheels, while the ICE acts as a generator to power the electric motor or charge the battery. This is less common but used in some PHEVs, like the BMW i3.
- Split-Parallel Hybrid: Combines aspects of both parallel and serial configurations, offering flexibility in different driving scenarios. This is used in some models like the Toyota Prius Prime.

In terms of their pros and cons, the series hybrid configuration is primarily utilized in heavy vehicles, military vehicles, and buses. Conversely, parallel and series-parallel configurations are mainly employed in smaller vehicles, such as passenger cars [4], [5].

D. OTHER VARIATIONS

- Micro Hybrid (μHEV): Like MHEVs but with even smaller electric motors and batteries, offering minimal fuel efficiency benefits [4].
- Range Extender Hybrid (REEV): Like PHEVs but with smaller batteries and an ICE primarily used to extend the electric range when needed. This is seen in models like the Chevrolet Volt.

E. BEYOND THESE, THERE ARE ONGOING DEVELOPMENTS IN HYBRID TECHNOLOGY, INCLUDING

- High-Voltage Hybrids: Utilize higher voltage systems for improved performance and efficiency [5].
- Full Electric Vehicles (EVs) with Range Extender: Like REEVs but with larger batteries and primarily operating as EVs with the ICE as a backup.

Choosing the right HEV variation depends on individual needs and driving habits. Consider factors like desired electric range, fuel efficiency, budget, and car. While fuel efficiency is a major draw, HEVs offer a wider range of benefits, from energy recovery and quieter operation to a more efficient and potentially more reliable power train. These hidden advantages make HEVs a compelling choice for those seeking a more sustainable and environmentally conscious driving experience. This survey dives deeper into how existing energy management strategies (EMS) are being used in HEVs. It goes beyond just summarizing these techniques by exploring how they're adapted for new technologies and different driving conditions. By examining current research, the survey also identifies areas where these strategies can be improved. This paves the way for developing entirely new EMS that take advantage of emerging technologies, ultimately pushing the boundaries of HEV energy management.

II. CONTROL STRATEGIES

Significant advancements in fuel economy and emission reduction have been the improvements in the HEVs by maintaining the power demand and vehicle performance [6]. Achieving optimal fuel economy and emissions reduction in hybrid vehicles relies on effectively managing the power distribution between the fuel cell and battery models. To meet this requirement, various control strategies for power split have been developed. Vehicle power demand, battery SOC, Vehicle speed, road load, and synchronous data from GPS about the traffic are the input variables of a typical power split controller. The set of decisions generated by the controller determines whether the vehicle should function within predetermined modes. The classification of HEV control strategies can be categorized into Online and Offline control strategies, as illustrated in Fig. 1.

A. OFFLINE STRATEGIES

In optimization-based control strategies, control signals are decided based on either global or local optimizations. Global optimization involves minimizing the sum of the objective function over time, while local optimization focuses on minimizing the objective function instantaneously.

Global optimal techniques rely mostly on the entire driving cycle, which becomes a non-causal system that is not practical in real time. However, most optimization techniques consider it to be a guiding technique for all other causal techniques. A few of the global optimization techniques discussed here are Linear programming, Dynamic programming, stochastic control strategies, and genetic algorithms.

1) LINEAR PROGRAMMING

It is applied to address and approximate the non-linear fuel consumption in HEVs, aiming to achieve a globally optimal solution. Kleimaier and Schroder introduced a convex optimization technique for propulsion capability analysis within the context of HEVs [7]. In their work, a steady and potent controller was formulated by Pisu et al., utilizing matrix linear inequalities to minimize fuel consumption [8].

2) DYNAMIC PROGRAMMING

A method pioneered by Richard Bellman is a technique employed to uncover optimal control policies in multi-stage decision-making scenarios that lead to the same optimal control policies but provide distinct results. The backward method calculates optimized results from each state to its end, while the forward method determines optimal values from initial states to all subsequent stages. Dynamic programming is versatile, as it can be employed in both linear and non-linear systems, and it can handle problems with constraints as well as unconstrained situations.

It offers optimal control strategies for power allocation among the ICE and the motor. However, it has two limitations: it requires prior information of the complete drive cycle and faces design challenges due to large dimensionality. Despite these setbacks, dynamic programming serves as a benchmark and a foundation for developing sub-optimal controllers.

Several studies have applied dynamic programming in HEV energy management. For instance, Brahma et al. used it in series HEV to achieve real-time optimal power distribution [9]. Wang and Jiao derived optimal control rules from dynamic programming to enhance a rule-based controller, leading to enhanced fuel economy [5]. In a separate study, heuristic control rules obtained from dynamic programming were applied across various driving cycles, resulting in a performance improvement that narrowed the gap compared to the optimal controller by 50-70%.

Kum combined dynamic programming with rule-based control to manage charge-sustaining control in HEVs [10], [11]. Kum applied dynamic programming to maintain battery energy levels within specified limits without negatively impacting battery health [11]. Computationally efficient algorithm for managing power in Plug-in Hybrid Electric Vehicles (PHEVs). Initially, Complicated dynamic programming was used to plan fuel and battery use for the entire trip. Gong and Li recently made changes, dividing the trip into smaller segments with fixed lengths.

For each segment, fuel use and battery level for different speeds and power-mixing ratios (engine vs. battery) are calculated. Instead of considering time, the best sequence of segments (like choosing puzzle pieces) to minimize fuel use throughout the trip is found.

Simplified dynamic programming within this "spatial domain" to further optimize, accepting a slight fuel efficiency trade-off compared to original dynamic programming, is used [12]. Pre-calculated segments and spatial optimization greatly improve speed compared to full dynamic programming.

The effectiveness of simplified macro-SOC profiles by applying a two-scale dynamic programming (DP) algorithm to three versions of the profile, each generated using different segmentation lengths (100m, 200m, 300m). They used the actual speed data from the first day as input for the two-scale DP simulations.

To summarize, dynamic programming is a powerful tool in HEV energy management, despite its limitations, and has been applied in various studies to improve energy efficiency and control strategies in hybrid vehicles.

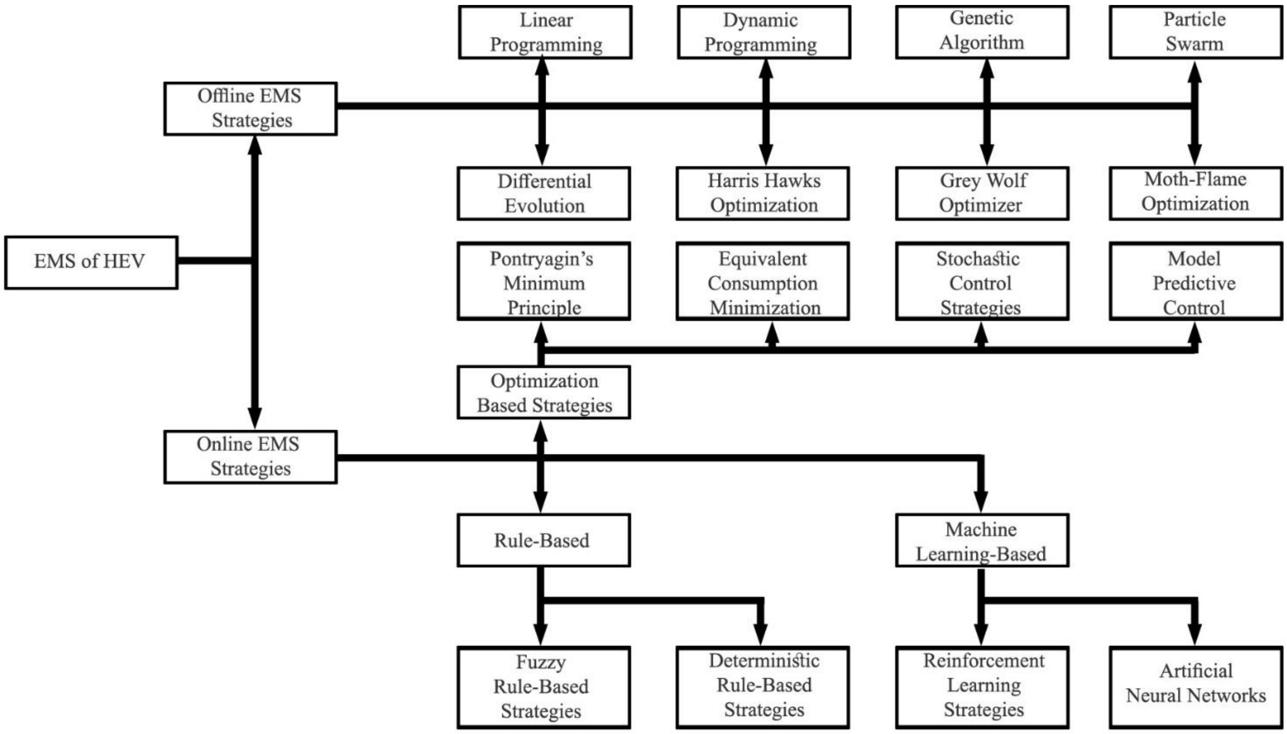

FIGURE 1. Different approaches are used to manage energy flow and power in hybrid vehicles.

3) GENETIC ALGORITHM

GA is increasingly used in energy management systems (EMS) of HEVs due to their ability to optimize complex and non-linear systems. GA is inspired by the principles of natural selection and evolution [13]. They work by generating a population of potential solutions (chromosomes). Each chromosome represents a set of control parameters for the EMS. Once the control parameters are set, the fitness of each chromosome will be evaluated. This is done by simulating the HEV's performance with that set of control parameters and measuring desired outcomes like fuel economy, emissions, or drivability. Then, chromosomes are selected based on their fitness. More fit chromosomes are more likely to be selected for reproduction. Crossing over and mutation of selected chromosomes is the next step in the process. This introduces variations in the next generation, allowing the algorithm to explore different control strategies. The process is repeated until a satisfactory solution is found [1].

4) PARTICLE SWARM OPTIMIZATION (PSO)

It is a computational technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by the collective behavior of bird flocks. It iteratively refines candidate solutions within a specified search space based on their quality. PSO serves as a versatile meta-heuristic approach suitable for optimizing non-differentiable problems characterized by noise or irregularities. Its effective implementation expands to the domain of HEVs. In a particular study, an enhanced PSO approach optimized a multilevel hierarchical control strategy for a parallel HEV, depicted in Fig. 2,14. This optimization led to improved coordination among the engine, electric motor, and battery, resulting in reduced fuel consumption and emissions. Another application involved Junhong utilizing PSO to address an HEV energy management problem, successfully achieving the simultaneous minimization of fuel consumption and emissions.

Rathor and Saxena proposed a PSO-based control strategy to optimize fuel consumption and emissions in HEVs, demonstrating notable enhancements in fuel economy during high-speed driving cycles and reduced emissions during middle or low-speed driving cycles [15]. Wu et al. utilized Particle Swarm Optimization (PSO) to optimize both the membership function and rules within a fuzzy logic-based HEV controller. This application resulted in the generation of near-optimal charge-sustaining control signals.

Additionally, Al-Aawar et al. and Wu et al. employed PSO to size electromechanical components, aiming to enhance efficiency and reduce fuel consumption. The design optimization environment included a PSO module and an electromagnetic-team fuzzy logic (EM-TFL) module [16]. The PSO optimizer explored the EM-TFL algorithm's database to identify the optimal population, aligning it with the objective functions illustrated in Fig. 3 [16]. A PSO candidate was considered successful if the degree of match surpassed the current tolerance. Successful candidates from all components were collected, and a global optimum was determined using a PSO method, as depicted in Fig. 4 [15].

TABLE 1. Comparison of advantages and disadvantages of offline EMS in HEV.

Offline strategy	Advantages	Disadvantages	References
Linear Programming	Easy to understand and fine-tune for specific needs. Fast solution times for real-time applications. Adaptable to various HEV designs and objectives. Guarantees the best solution within defined constraints.	Struggles with non-linear relationships in HEVs. Can become computationally expensive for large problems. Accurately representing real-world complexities can be difficult. Might not seamlessly integrate with other control algorithms.	[7], [8], [17], [18], [19], [20], [21], [22]
Dynamic Programming	Easy to understand and has the potential for computational efficiency in real-time control. However, its real-time performance is influenced by factors such as the solution step size, the dispersion degree of state variables, and boundary conditions. Smaller step sizes and highly dispersed state variables can increase computational complexity, while appropriate boundary conditions can help maintain efficiency. Tailorable to specific vehicle goals and constraints. Guarantees the best solution within defined limitations.	Struggles with non-linear aspects of HEVs, potentially reducing accuracy. Can become computationally expensive for large problems. Capturing real-world HEV behaviour can be difficult. May not easily integrate with other HEV control algorithms.	[5], [9], [10], [11], [12], [23], [24], [25], [26]
Genetic Algorithm	Offers transparency and readily adapts to vehicle specifics and goals. Solves problems efficiently for real-time power adjustments.	Struggles with non-linearities in HEVs, impacting precision. Calculations can become demanding with increasing problem size. Capturing real-world HEV behaviour can be intricate. May require extra work to integrate with other control algorithms.	[1], [13], [27], [28], [29]
Particle Swarm	Clear and explainable decision-making. Fast computation for real-time power management. Adaptable to different objectives and constraints. Guaranteed optimal solution under specific conditions	Can't handle complex HEV dynamics like battery degradation. Computationally expensive for complex problems. Accurately modeling real-world HEV behaviour is challenging. Integration with other HEV control algorithms might be difficult. These challenges arise due to PSO's stochastic nature, which can lead to inconsistent optimization results. Additionally, PSO often requires extensive tuning of parameters to achieve optimal performance, which can be time-consuming and complex. Furthermore, PSO may struggle with high-dimensional search spaces and can be computationally intensive, making real-time implementation challenging.	[2], [15], [16], [30], [31], [32], [33], [34]
Differential Evolution (DE)	Simplicity and ease of implementation. Global search capability. Few parameters. Robust performance. Parallelization	Parameter sensitivity. Convergence speed. No explicit handling of constraints. Lack of adaptivity. Scalability issues.	[35], [36], [37], [38], [39]
Harris Hawks Optimization (HHO)	Balanced exploration and exploitation. Simple and scalable. Dynamic behavior to escape local optima.	- Sensitive to parameter settings - Slow convergence in some cases	[40], [41], [42], [43]

TABLE 1. ***(Continued.)*** **Comparison of advantages and disadvantages of offline EMS in HEV.**

Grey Wolf Optimizer (GWO)	Strong global exploration ability. Simple and flexible. Good for multimodal problems	Slow convergence in later stages. May struggle with high-dimensional problems.	[44], [45], [46]
Moth-Flame Optimization (MFO)	Effective exploration. Good for nonlinear and multimodal problems. Simple to implement	Prone to premature convergence. Slower exploitation. Limited adaptivity	[47], [48], [49]

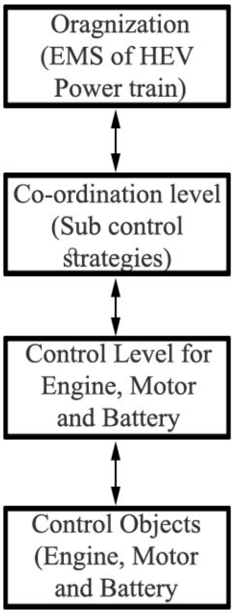

FIGURE 2. **Multi-level hierarchical EMS for parallel.**

Table 1. summarizes the advantages and disadvantages of offline strategies.

Table 2 covers various offline optimization algorithms, including their objectives, control strategies, factors considered, software used, and constraints handled. This table provides a comprehensive overview of different optimization algorithms for EMS in HEVs, highlighting their objectives, control strategies, factors considered, and the software used. It also outlines the constraints each algorithm considers, helping to illustrate how they handle various aspects of energy management in electric vehicles.

B. ONLINE CONTROL STRATEGIES

HEVs are real-time and causal, unlike their offline counterparts. These strategies can be rule-based, employ heuristic control rules, or involve instantaneous optimization of a specified objective function.

1) RULE-BASED CONTROL STRATEGIES

It is a prevalent method for real-time supervisory control in HEVs. These control algorithms often rely on heuristics, engineering intelligence, or mathematical models to optimize the internal combustion engine's efficiency while enabling energy recovery through regenerative braking [50], [51]. The development of rule based HEV control involves creating rules for powertrain management and calibrating the strategy through simulations on a vehicle model. However, rule-based approaches may not guarantee optimality or meet integral constraints like charge sustainability.

To address this, control rules must be revised to ensure the integral constraint (State of Charge, SOC) remains within specified limits. While there is no standard method for formulating control rules, they can be made complex enough to account for various exceptional occurrences that may affect the vehicle [52]. The simplicity of rule based HEV management makes them easy to implement on actual vehicles. Despite their widespread use due to minimal computational demands, natural applicability to online applications, high reliability, and reasonable fuel consumption outcomes, rule-based HEV management approaches require periodic revisions.

The lengthy rules creation and calibration process, along with the need for rewriting rules for each new driving scenario and powertrain, raise concerns about their robustness [53]. Research indicates that rule-based systems yield acceptable but poorer fuel consumption outcomes compared to optimization methods. Rule-based controllers are further classified into deterministic and fuzzy rule-based control strategies.

a: DETERMINISTIC RULE-BASED CONTROL STRATEGY

Deterministic rule-based control strategies aim to achieve optimal fuel economy or emissions by relying on pre-computed look-up tables. This approach is effective in determining optimal settings for various parameters, such as CVT gear ratio, motor torque, and engine throttle, in real time.

One of the successful deterministic rule-based HEV control systems is the electric assist control method [54]. In this approach, the electric motor serves as the primary power source (ICE) and is engaged only when necessary. This method has proven effective in optimizing fuel efficiency.

Another variant is the thermostat control technique, where the electric motor and internal combustion engine work together to generate electrical energy for vehicle propulsion. By cycling the internal combustion engine on and off, this technique maintains the battery state of charge within specified high and low values. However, it's worth

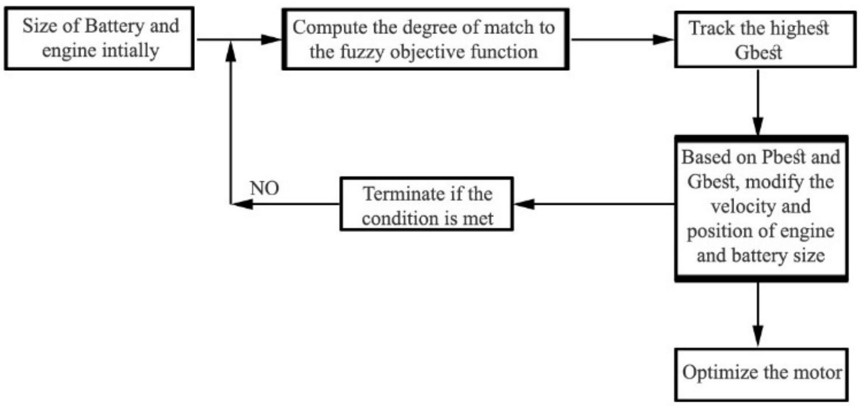

FIGURE 3. EM-TFL optimization environment HEV.

TABLE 2. Summary table of offline EMS in HEV.

Algorithm	Objectives	Control Strategies	Factors Considered	Software Used	Constraints Considered
Model Predictive Control (MPC)	Minimize energy consumption, maximize efficiency	Predictive control based on the system model	Battery state, driving patterns, vehicle dynamics	MATLAB, Simulink	Battery capacity, range limitations, driving conditions
Dynamic Programming (DP)	Optimize battery usage, extend range	Sequential decision-making over time	Energy consumption, regenerative braking, driving profile	MATLAB, Python	Battery constraints, power limits, load profiles
Genetic Algorithm (GA)	Optimize energy distribution, fuel efficiency	Evolutionary optimization	Vehicle parameters, driving conditions, fuel efficiency	MATLAB, Python	Battery life, fuel consumption, operational limits
Particle Swarm Optimization (PSO)	Minimize energy consumption, improve battery life	Swarm-based search	Battery performance, driving patterns, vehicle efficiency	MATLAB, Python	Battery constraints, vehicle performance limits
Differential Evolution (DE)	Minimize energy consumption, optimize performance	Mutation and crossover-based optimization	Battery state, driving conditions, energy efficiency	MATLAB, Python, C++	Battery life, performance constraints, energy usage
Harris Hawks Optimization (HHO)	Optimize battery management, improve efficiency	Predatory behavior-based optimization	Energy consumption, battery state, vehicle dynamics	MATLAB, Python	Battery constraints, operational limits, efficiency
Grey Wolf Optimizer (GWO)	Minimize energy consumption, enhance performance	Social hierarchy-based optimization	Battery performance, driving patterns, efficiency	MATLAB, Python	Battery capacity, energy constraints, vehicle limits
Moth-Flame Optimization (MFO)	Optimize energy usage, battery life	Swarming behavior-based optimization	Energy consumption, battery state, driving conditions	MATLAB, Python	Battery life, energy constraints, operational limits

noting that the thermostatic control technique has demonstrated sub-optimality when compared to other deterministic rule-based control systems [55]. Common deterministic rule-based control strategies include:

1. Exclusive Electric Vehicle (EV) Mode: Operate the vehicle solely in electric mode when power requirements are below a specific threshold. This rule is designed to avoid inefficient engine operating points, with its effectiveness depending on the electric motor and battery sizes.
2. Electric Motor Assistance: Help with the electric motor if the power demand of the vehicle exceeds the permitted engine power.
3. Regenerative Braking: Charge the battery using regenerative braking to capture and store energy during deceleration.

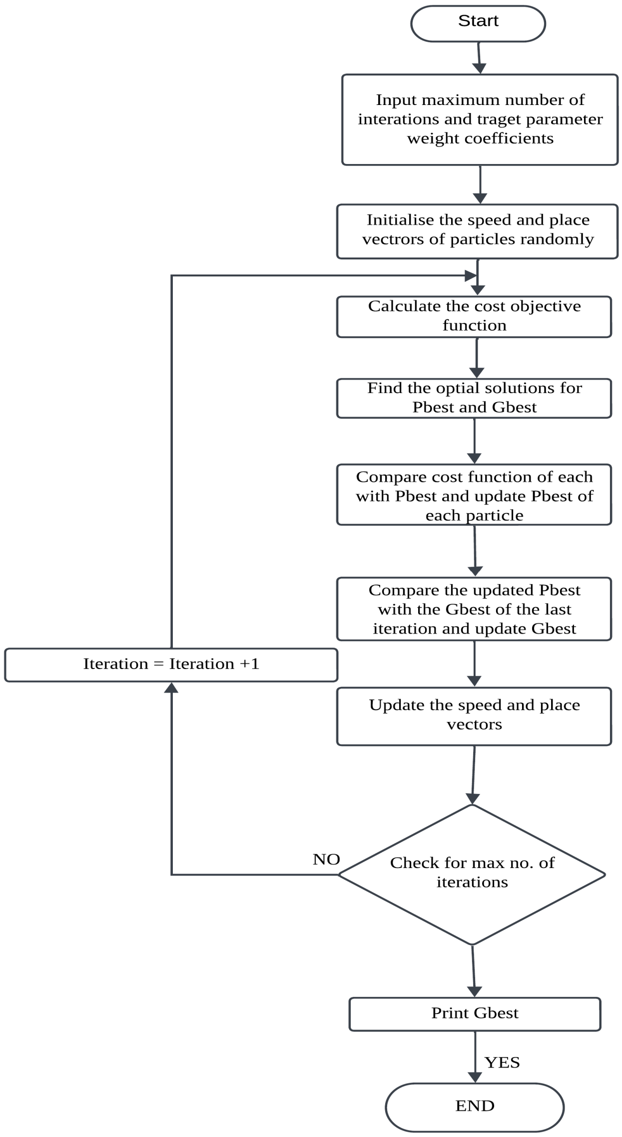

FIGURE 4. Global optimal solution using PSO.

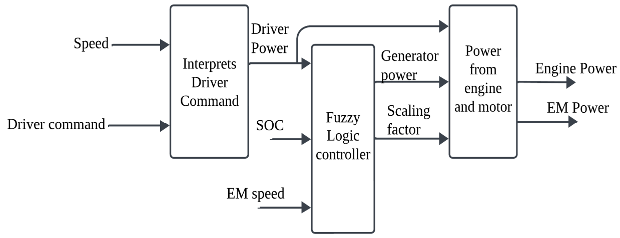

FIGURE 5. A simple fuzzy logic controller.

Torque Boost for SOC Maintenance: Produce additional torque to ensure the battery's state of charge remains above a predetermined minimum value. These deterministic rule-based control strategies are employed to optimize the operation of HEVs in real-time, focusing on achieving the best balance between fuel efficiency, emissions, and overall system performance.

b: FUZZY RULE-BASED CONTROL STRATEGY

Fuzzy rule controllers represent a control strategy that transforms linguistic descriptions of control inputs into numerical values through the processes of fuzzification and defuzzification [56]. These controllers utilize multivalued logic derived from fuzzy set theory to handle approximate reasoning. The simplicity of fuzzy rule controllers allows for effective tuning and adaptation, providing increased control flexibility. They find applicability in intricate systems such as advanced powertrains, where inputs like battery state of charge, desired internal combustion engine (ICE) torque, and intended mode are processed to determine the ICE operating point. Fuzzy sets encompass variables such as driver command, battery state of charge, and motor/generator speeds. Some frameworks also incorporate a power notification system to facilitate high-efficiency engine operation, as depicted in Fig. 5 [57]. Various versions of fuzzy rule-based control include traditional, adaptive, and predictive strategies.

Traditional Fuzzy Control Strategy:

It enhances efficiency, which allows ICE to operate more effectively. This is achieved through load balancing, where the electric motor guides the engine to operate within its most efficient range while also maintaining the battery's charge. Wang et al. introduced a fuzzy logic controller designed to optimize fuel consumption in a parallel HEV, focusing on the efficiency optimization of critical components such as the internal combustion engine, electric motor, and battery [58]. The approach involves utilizing a primary compression ignition direct injection (CIDI) engine efficiency map, with the fuzzy controller monitoring individual components to operate close to the ideal curve [59]. The process includes translating inputs from the accelerator and brake pedals into the driver's power command and using this command in conjunction with the battery and other components. Torque distribution control using fuzzy logic is evaluated in a parallel hybrid vehicle under the FTP75 urban driving cycle. Different fuzzy rule sets are applied to each energy management strategy within the FTDC. The vehicle's performance adheres to the fuzzy rule set that reflects the driver's preferences. The study shows that vehicle performance, including fuel economy, emissions, and battery state of charge (SOC), is highly dependent on the chosen energy management strategy [60].

Adaptive Fuzzy Control Strategy:

Because of its ability to improve fuel efficiency and emissions, the adaptive fuzzy control approach is gaining favour for automotive applications like HEVs [61]. This strategy is especially beneficial if fuel efficiency and pollution are frequently competing goals, making it hard to obtain an ideal solution. However, a suboptimal solution can be obtained using the weighted-sum technique, in which suitable weights are modified for varied driving situations [62]. Individual objectives can be controlled by adjusting the weights allocated to them. Adaptive fuzzy logic controllers are

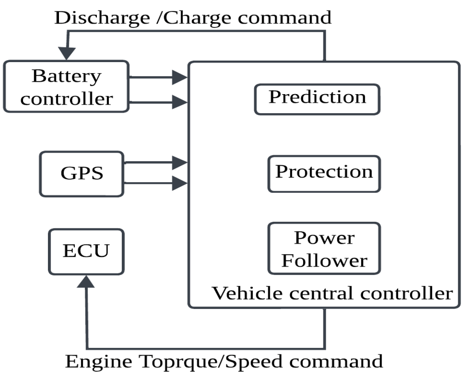

FIGURE 6. Predictive fuzzy logic controller with GPS.

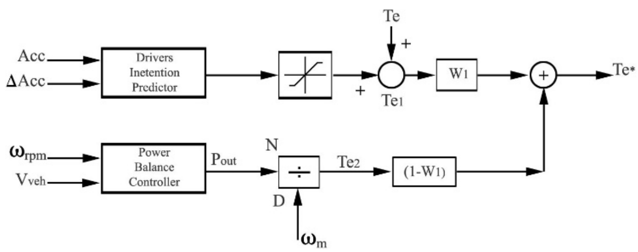

FIGURE 7. Fuzzy logic controller and by Lee et al.

documented in the literature for handling conflicting objective control issues.

Predictive Fuzzy Control:

This method utilizes pre-existing information regarding a planned driving route, often obtained through a Global Positioning System (GPS), as shown in Fig. 6 [63]. This data is typically collected by considering the vehicle's speed, speed conditions within a lookahead window, and the altitude of sampled locations along a predefined path. In this approach, the predictive fuzzy controller assesses the suitable internal combustion engine (ICE) torque contribution at each vehicle speed. It then generates a normalized signal within the range of -1 to $+1$, indicating whether the power source should be charged or discharged [64]. Due to their simplicity and robustness, fuzzy controllers have attracted the attention of professionals in heuristic control, particularly in the fields of study and automobile industries. Arsie and colleagues employed a fuzzy controller to regulate parameters related to the driver-vehicle interface, torque administration, and battery recharging. Their suggested driver model utilized fuzzy control principles, providing a realistic representation of a human driver and achieving a perfect match between the goal and immediate vehicle speed. Kakouche et al. proposed a robust and unaffected-by-vehicle-load-change fuzzy logic controller, as depicted in Fig.7 [65].

Baumann et al. demonstrated the effectiveness of fuzzy controllers in improving fuel economy, proving their suitability for nonlinear, multi-domain, and time-varying systems [65], [66]. Their control strategy encouraged most operating conditions to be near the most efficient point, resulting in an increase in mean efficiency from 23% to 35.4% across the nation's urban driving schedule. Fig. 8a and 8b illustrate a PID-like fuzzy controller developed by Stockar et al., featuring intuitive, functional scaling that is easy to tune even without a vehicle mathematical model [67].

Proportional-integral (PI) controllers have also demonstrated success in nonlinear plant control. Syed et al. optimally planned a HEV's engine power and speed using a fuzzy-gain scheduling technique. Jianlong et al. aimed to develop a highly computational fuzzy control approach with a two-input, one-output network topology. Zhou et al. employed particle swarm optimization to enhance the accuracy, flexibility, and resilience of a fuzzy control method.

Kakouche et al. proposed a predictive fuzzy logic controller to manage power flow in a series HEV [65]. The regulations were set based on the vehicle's future state, considering road conditions and elevation locations. The output instruction indicated "high discharging" when the GPS showed "reducing elevation" and "growing traffic flow" for the future condition.

Considering the current vehicle condition, engine power demand, and available online driving cycle data, Zhang et al. introduced the concept of a fuzzy intelligent energy management agent (IEMA) for vehicle torque distribution and charge sustenance [28], [68], [69]. Niu et al. presented a digital adaptive intelligent fuzzy controller to optimally manage the Internal Combustion Engine (ICE) torque while minimizing competing objectives such as fuel consumption and pollution [70]. Fuzzy techniques are also applicable to non-control applications, such as developing HEV modeling software with versatile applications. Table 3. compares the advantages and disadvantages of rule-based strategies in the energy management of HEV.

2) ONLINE OPTIMIZATION-BASED STRATEGIES

Optimization systems, such as ECMS and PMP, transform global optimization issues into local ones, lowering computing effort and making them real-time implementable. Despite producing suboptimal outcomes, local optimization algorithms have received much interest in HEV control research. These solutions are intended to decrease global optimization while increasing HEV control efficiency.

a: PONTRYAGIN'S MINIMAL PRINCIPLE

Pontryagin's Minimum Principle (PMP), formulated in 1956 by the Russian scientist Lev Pontryagin and his students, is a specific instance of the Euler-Lagrange equation in the calculus of variations. It mandates that the optimal solution to a global optimization problem must satisfy the optimality criterion [82]. The PMP algorithm relies on the instantaneous minimization of a Hamiltonian function throughout a driving cycle. If the trajectory obtained by PMP is unique and adheres to the specified constraints and boundary conditions, it can be termed a globally optimal trajectory.

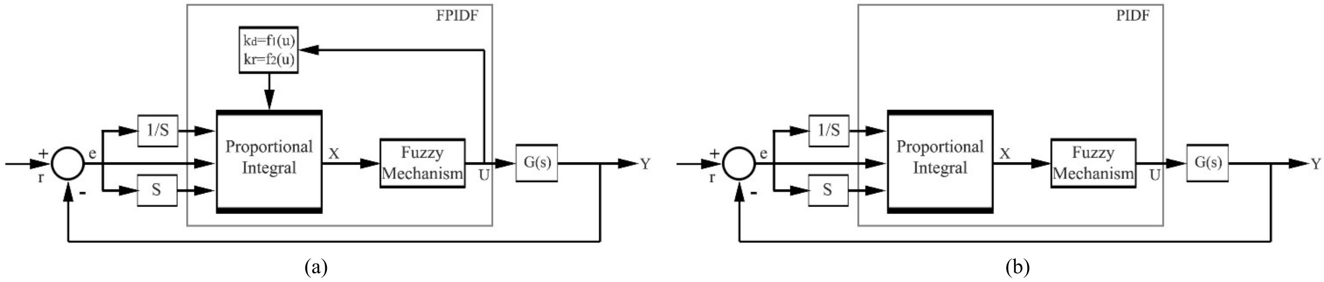

FIGURE 8. a. Block diagram of fuzzy controller with FPIDF. b. Block diagram of fuzzy logic controller with PIDF.

TABLE 3. Advantages and disadvantages of rule-based EMS strategies in HEV.

Rule Based Strategies	Advantages	Disadvantages	References
Traditional Fuzzy rule	Handles non-linearities well. Easy to understand and adapt. Robust to uncertainties. Fast computation.	Requires deep HEV knowledge for rule design. Subjective rule design impacts performance. Tuning membership functions and weights is tricky. Can become cumbersome with added complexity.	[12], [57], [58], [60] [71], [72], [73], [74]
Predictive Fuzzy rule	Fuzzy logic excels in complex HEV systems with imprecise factors. Rules based on expert knowledge are easy to understand. Tolerates imprecise data for real-world driving. Simple rules enable faster execution.	Requires deep understanding and expert knowledge. Different interpretations can impact performance. Optimizing rules can be intricate and subjective. Adding complexity can lead to cumbersome maintenance.	[63], [75], [76], [77], [78]
Adaptive Fuzzy rule	Handles non-linearities in HEV systems. Intuitive and interpretable, based on expert knowledge. Robust to uncertainties in real-world driving. Fast computation compared to complex algorithms.	Requires deep understanding and expert knowledge to design effective rules. Subject to subjectivity in rule design, impacting performance. Tuning membership functions and weights can be challenging. Limited scalability as complexity increases.	[73], [74], [75], [76], [77], [78], [79], [80], [81]
Deterministic Rule based	Handles non-linearities effectively. Intuitive and interpretable due to human-like rules. Robust to uncertainties in real-world driving. Fast computations compared to complex algorithms.	Requires deep HEV expertise for rule design. Subjectivity in rule design can impact performance. Tuning membership functions and weights can be tricky. Scalability is limited as complexity increases.	[71], [73], [75], [80], [81]

Kim et al. applied PMP to identify the optimal control law for a PHEV, as illustrated in Fig. 9,83. They demonstrated this by establishing an accurate initial estimate. The study revealed that when state boundary requirements are met, the immediate reduction of the Hamiltonian function across a driving cycle yields a control strategy that closely resembles the findings of dynamic programming.

Stockar et al. devised a model-based control technique for a PHEV inspired by Pontryagin's Minimum Principle (PMP) with the aim of reducing CO2 emissions. They observed a significant dependency of the PMP controller's efficiency on the anticipated co-state value [83]. In their model-based PMP control approach, the vehicle is directed to deplete the battery when the co-state value surpasses 10. Once the reduced State of Energy (SOC) constraint is encountered, the mode transitions into a charge-sustaining state. Their conclusions suggest that PMP operates as a shooting technique, dealing with a boundary value optimization problem, resulting in a non-causal and non-real-time optimal control approach [84].

TABLE 4. Comparison of online optimization strategies.

Optimization Based Strategies	Advantages	Disadvantages	References
Pontryagin's minimum principle	Finds mathematically optimal control for defined goals and constraints. Suitable for non-linear HEV systems with dynamic power flows. Adapts to various objectives (fuel economy, performance) and constraints. Well-established framework for rigor and understanding.	Solving equations can be demanding, especially for real-time use. Requires careful initial conditions for optimal solution. Relies on accurate parameters, often challenging to obtain in real-time. Translating theoretical solutions to practical control strategies can be intricate.	[101], [102], [103], [104], [105]
Equivalent Consumption Minimization	Easy to implement and works in real-time. Adaptable to various HEVs and objectives. No need for future predictions.	May not be optimal over long distances. Can harm battery life with frequent cycles. Ignores energy sources beyond ICE and battery. Relies on accurate conversion factor calibration.	[82], [85], [86], [87], [106], [107], [108]
Stochastic Control Strategies	Adapts to unpredictable driving conditions, potentially achieving better fuel economy or emissions reduction. Flexible to different scenarios and user preferences for personalized control. Robust to uncertainties, improving reliability and consistency.	Computationally demanding, potentially unsuitable for real-time applications. Relies heavily on accurate data, which can be challenging to acquire and maintain. Complex to design and analyze, requiring specialized expertise. Integrating with existing control systems can be difficult.	[14], [15], [89], [90], [91], [109], [110], [111], [112]
Model Predictive Control	Optimizes fuel, emissions, or other objectives while adapting to system constraints and driving conditions. Effectively manages non-linear dynamics inherent to HEVs. Uses future predictions for proactive power management and improved performance. Resists uncertainties and disturbances for reliable real-world performance.	May not be suitable for real-time control with strict computational limits. Relies on an accurate and complete HEV model for optimal performance. Requires balancing prediction accuracy with computational burden. Parameter and cost function tuning demands expertise and time. Integration with existing control systems can be complex.	[28], [83], [84], [90], [92], [93], [94], [95], [96], [111], [113], [114], [115], [116], [117]
Artificial Neural Networks	Continuously improve decisions for complex HEV systems. Robust to various driving conditions and disturbances. Promise real-time decision-making for dynamic energy management.	Lack of transparency raises safety and accountability concerns. Require substantial data for effective training. Complex architectures can strain resources. Can lose generalizability if trained too closely to data.Specialized knowledge hinders wider adoption.	[77], [85], [97], [98], [99], [118], [119], [120], [121]

b: EQUIVALENT CONSUMPTION MINIMIZATION STRATEGY

The Equivalent Consumption Minimization Strategy (ECMS) functions as a local optimization approach aimed at reducing fuel consumption and emissions of pollutants in HEVs. ECMS is grounded in the heuristic assumption that the energy used to propel a vehicle over its driving cycle ultimately originates from the engine, with the hybrid system acting as an energy buffer [85]. It involves the immediate reduction of a cost index, which is the sum of various operational indicators adjusted by equivalence factors. Commonly used variables in ECMS HEV control include the turbine cost of fuel and battery fuel cost.

Several modifications to the ECMS optimization control technique have been proposed, including Adaptive ECMS and Telemetry ECMS. These variations adjust the equivalency factor based on historical driving data and future projections. However, these adaptive strategies require the use of predictive technologies such as GPS, incurring additional expenses.

Paganelli et al. applied an ECMS technique to reduce fuel consumption and pollutant emissions in a charge-sustaining sport utility vehicle [85]. The results demonstrated that the ECMS technique could lead to a charge-sustaining reduction in emissions without adversely affecting fuel efficiency. Similar outcomes were observed by Gu et al. and Rousseau et al., indicating that ECMS consistently produces near-optimal fuel economy results, even in the absence of detailed operating information.

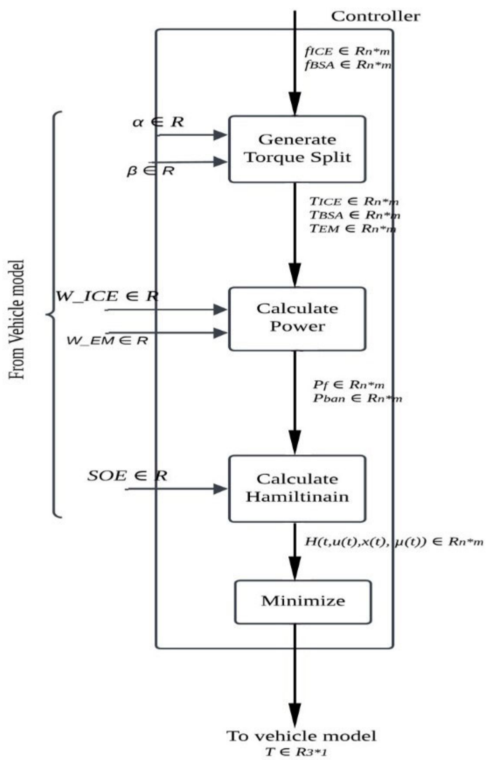

FIGURE 9. Flowchart of Model-based PMP control strategy.

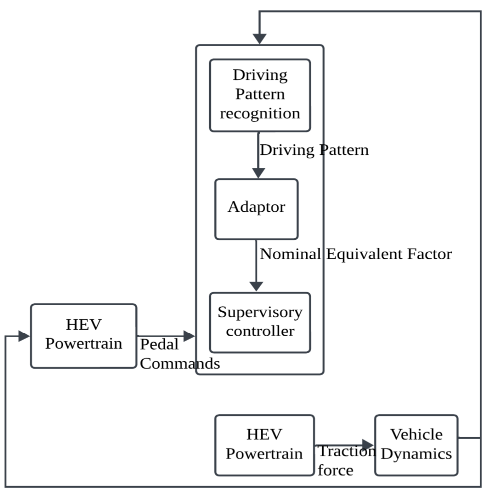

FIGURE 10. DPR approach to EMCS real-time adaption.

Hwang et al. recommended an adaptive Equivalent Consumption Minimization Strategy (A-ECMS) for real-world energy flow management in a HEV [86]. This technique dynamically adjusts the controlling parameter (equivalence factor) in response to varying road load conditions.

This approach continuously adjusts the control parameter (equivalence factor) based on road load conditions, generating charge-sustaining quasi-optimal control signals. Fig.10. illustrates that Gu et al. introduced the driving pattern recognition (DPR) technique to enable real-time adaptation of ECMS, enhancing the estimation of the equivalency factor under diverse driving situations.

Yang et al. devised a multi-objective nonlinear ECMS that transforms a multi-objective nonlinear optimal torque distribution approach into a single-objective linear optimization problem [87], [88]. Simulation data indicates that linearizing a nonlinear optimization problem can reduce computation time by up to 38% compared to typical drive cycles, with minimal or no compromise on the achieved optimization solution. Olin et al. developed an ECMS strategy to improve fuel efficiency by predicting equivalency parameters using the known total trip distance rather than driving pattern data [88].

c: STOCHASTIC CONTROL STRATEGY

It is used to find the optimal solution having uncertainties. Random Markov process is used to model the vehicular power demand, using which future power demand can be predicted [89]. This leads to the acquisition of the optimal control strategy utilizing stochastic dynamic programming (SDP), presented in its complete steady-state form, making it directly implementable on vehicles. Applying SDP, Lin et al. employed an engine-in-loop system to assess the influence of transients on engine emissions. A comparison was made between two variants of SDP, namely infinite horizon and short path SDP, in the context of HEVs [15], [90]. The results indicated that the short-path HEV exhibited more optimal outcomes. This was attributed to the fewer parameters requiring tuning in this test, coupled with a more favorable battery State of Charge (SOC) [91].

d: MODEL PREDICTIVE CONTROL STRATEGY

Model Predictive Control (MPC) is an approach to derive a control signal that minimizes the objective function by employing a plant process model. It operates in real time by predicting the impact of a control input on the system output using a model [92]. The essence of MPC lies in calculating the optimal control for the prediction horizon in real time and implementing only the first element. MPC heavily relies on high model accuracy and prior knowledge of reference trajectories, aspects that are not readily attainable in vehicular applications.

MPC has proven to be effective, saving up to 31.6% more gasoline compared to rule-based control techniques. Although MPC has been less commonly applied to control the energy of HEVs, Justo et al. introduced an MPC energy management approach for a parallel HEV [64]. They utilized GPS data to determine the road grade over the predicted horizon and maintained a constant vehicle speed in their analysis. The optimal control sequence minimizing fuel usage was then computed using dynamic programming [93]. According to simulation data, the model predictive controller can achieve up to 20% gasoline savings by extending the prediction horizon throughout the entire journey.

In the study conducted by Chen et al., Model Predictive Control (MPC) is employed to enhance battery life, extend driving range, and simultaneously reduce pollutants, fuel

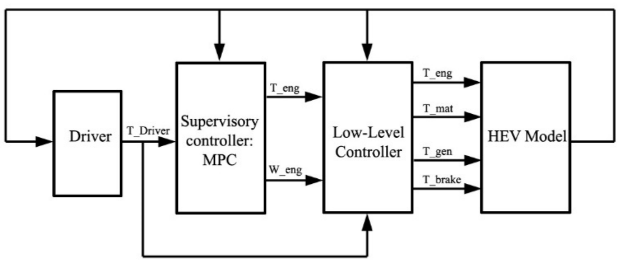

FIGURE 11. Borhan's two-phase MPC strategy.

consumption, and drivetrain oscillations in HEVs [94]. In another investigation by Rajagopalan et al., traffic data, including road speed limits and topological information from GPS, are utilized alongside a fuzzy logic controller. This combination is used to determine the power split between the internal combustion engine and the electric motor based on considerations of efficiency and emissions.

For the control of parallel HEVs, Sciaretta et al. and Borhan et al. introduce an MPC framework that doesn't require knowledge of future driving conditions. Simulation results, particularly during an ECE driving cycle, reveal a noteworthy 50% reduction in fuel consumption compared to a typical urban driving scenario [90], [95].

Ripaccioli et al. presented a hybrid MPC technique to coordinate powertrains and impose state and control limitations. Ripaccioli et al. established a stochastic model predictive control (SMPC) paradigm for the power management of a series HEV in another investigation. When compared with deterministic receding horizon control approaches, simulation results reveal that the SMPC system drives engine, motor, and battery functions through a causal, time-invariant, state-feedback manner, resulting in enhanced fuel efficiency and vehicle performance [90].

In the work by Vogal et al., a predictive Model Predictive Control (MPC) model is formulated, utilizing driving route prediction, and optimized through inverse reinforcement learning for the purpose of fuel economy optimization. Borhan et al. also contribute to the field by introducing a sophisticated two-phase MPC control approach designed for a power split HEV, as depicted in Fig. 11. When applied to a linear time-varying MPC strategy; this suggested two-step nonlinear MPC technique demonstrates a substantial improvement in fuel efficiency across standard driving cycles [95].

Poramapojana et al. present another MPC-based control method focused on minimizing fuel consumption and sustaining charge based on future torque demand projections, as illustrated in Fig. 12. Simulation results indicate that the proposed method has the potential to significantly enhance fuel economy compared to conventional driving cycles [96].

e: ARTIFICIAL NEURAL NETWORKS

Imagine a system for computing that resembles the human brain, where linked processing units interact with each other and adapt to incoming information. This is the essence of an

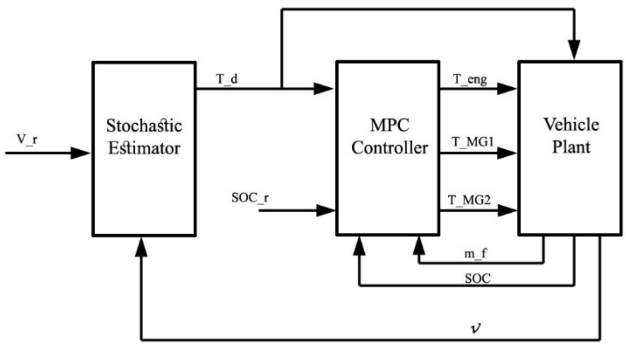

FIGURE 12. MPC-based control method.

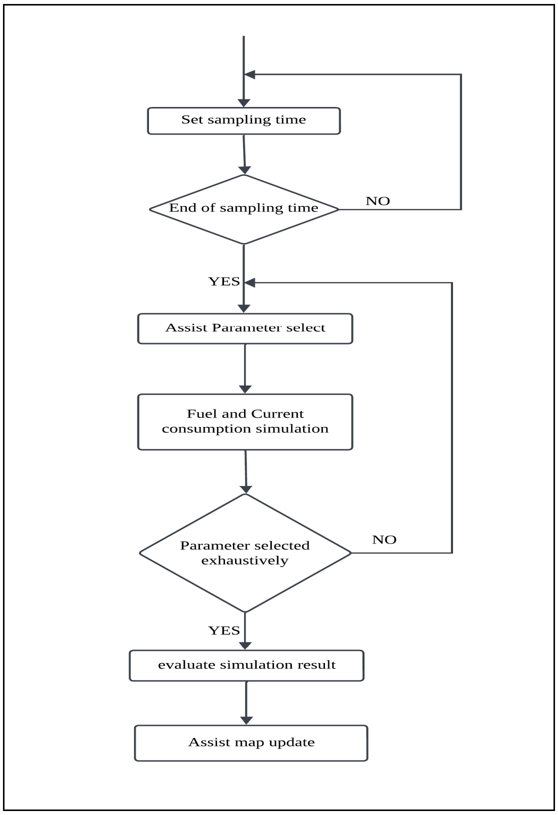

FIGURE 13. Neural Fuzzy controller.

artificial neural network, brought to life in 1943 by McCulloch and Pitts, and further revolutionized by Hebb's learning rule in 1949 [97]. The back-propagation approach allows ANN to be taught to comprehend an extremely non-linear input/output connection. Because of its adaptive structure, it is well-suited for HEV management of energy applications since it allows for the learning and replication of non-linear correlations among the inputs and results of an established energy management network.

Several studies have been conducted to create control systems that integrate ANN with fuzzy logic to increase fuel costs and minimize pollution for various drivers and operating models.

TABLE 5. Comparison of different parameters in the implementation of various control strategies in HEV in real time.

EMS	Mechanical complication	Analytical complication	Solution	Historical data requirement	Difficulty in real world implementation	Robustness
Linear Programming	No	Low	Optimal	No	Hard	Low
Dynamic Programming	Yes	High	Global	Yes	Very hard	Low
Genetic algorithm	Yes	Medium	Global	No	Hard	Medium
Particle Swarm Optimization	No	Medium	Global	No	Hard	Medium
Fuzzy rule based	No	Low	Global	Yes	Easy	High
Deterministic rule based	No	Very Low	Non-Optimal	Yes	Very easy	Medium
Pontryagin's minimum Principle	No	High	Optimal control	No	Medium	Low
Equivalent consumption minimization	Yes	Low	Local	No	Medium	Low
Stochastic control strategies	Yes	Medium	Near to optimal	Yes	Hard	High
Model predictive control	No	Medium	Global	No	Medium	Low
Artificial Neural Networks	Yes	Medium	No direct solution	Yes	Hard	High

For instance, Baumann developed a load-levelling approach that integrates Artificial Neural Networks (ANN) and fuzzy logic to implement a load-levelling strategy, aiming at increased fuel efficiency and reduced emissions across various drivers and driving patterns [98], [99]. Arsie et al. utilized a dynamic model to emulate the vehicle driveline, internal combustion engine, and electric motor/generator (EM). Mohebbi et al. proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller based on the required horsepower for driving and battery state of charge, aiming to maximize fuel efficiency and minimize emissions in a HEV [72]. Suzuki et al. improved the neural network control framework to accommodate multiple objectives, including velocity distribution optimization, fuel efficiency optimization, and reduction in electric current consumption [99]. Prokhorov et al. introduced a neural network-based regulator for the Toyota Prius HEV, built on a recurrent neural network and utilized in both online and offline training, resulting in a 17% improvement in average fuel economy across standard driving cycles. Gong et al. introduced an artificial neural network (ANN)-based model for highway journeys, leading to a notable improvement in the accuracy of trip modeling and fuel efficiency [25]. Additionally, Boyali et al. presented a technique based on neuro-dynamic programming (NDP) for real-time control of HEVs, illustrated in Fig. 13. However, simulation studies revealed that it achieved lower fuel economy compared to the ideal dynamic programming controller [76].

A few online energy management strategies are designed mainly to concentrate on cost minimization without power source degradation. To cluster the driving patterns, a map that self-organizes (SOM) is trained [100]. In this study, the SOM competitive layer is built of 10 driving parameters as inputs and classifies the driving patterns into three groups as output. Following that, the evolutionary algorithm designs and optimizes an offline three-mode fuzzy logic controller (FLC) for each driving pattern [79]. Unlike previous studies, the FLC output membership function is based on the online determination of the optimum power and effectiveness of the fuel cell system, which fluctuates over time. Table 4 compares and summarizes the advantages and disadvantages of online optimization strategies in the energy management of HEVs.

Table 5. shows the comparison of different parameters in the real-time implementation of offline and online (Rule-based and Optimization-based) control strategies.

III. OTHER RECENT TRENDS IN EMS STRATEGIES (DEEP AND REINFORCEMENT LEARNING)

Beyond the previously discussed broad categories of HEV control strategies, emerging research has yielded several recently developed techniques that warrant further investigation. In HEVs, optimizing the use of the electric motor and internal combustion engine for fuel efficiency and emissions reduction is crucial. This is where deep learning and reinforcement learning come in, offering promising control strategies for Energy Management Systems (EMS).

Neural networks can learn complex relationships between various aspects of HEV operation, like battery state, engine power, and driving conditions. This allows for more sophisticated decision-making compared to traditional rule-based systems. Examples include predicting future power demands, optimizing engine start-stop strategies, and managing battery degradation. The EMS acts as an agent in the HEV environment, continuously learning through trial and error [122]. Based on rewards (e.g., fuel efficiency) and penalties (e.g., emissions), the agent learns optimal control policies for

TABLE 6. Benefits and challenges of deep learning and reinforcement learning.

DL and RL	Benefits	Challenges	Use in HEV	References
Deep Q-Networks	Adapt to diverse driving scenarios by learning from experience, unlike rule-based systems that struggle with changing conditions. Multiple reward functions can be incorporated into the DQN, balancing fuel efficiency, emissions, and battery health. Make quick decisions based on current state information, improving overall system performance.	Extensive training data with diverse driving situations is necessary for achieving optimal performance. Running and training DQNs can be computationally expensive, requiring specialized hardware. Interpreting the DQN's decision-making process can be challenging, hindering further optimization, and debugging.	Deciding when to use the electric motor, engine, or both for optimal fuel efficiency. Maximizing energy recuperation during braking while considering battery state and driver comfort. Adjusting powertrain operation to minimize battery wear and tear while maintaining performance.	[67], [81], [118], [122], [124], [129], [130], [131], [132], [133], [134], [157]
Proximal Policy Optimization	Learn effectively from smaller datasets compared to some other DRL methods. Enforces a "proximity constraint" during policy updates, preventing drastic changes and improving training stability. Well-suited for problems with continuous action spaces, like adjusting engine power, making it ideal for HEV EMS.	Finding the optimal set of hyperparameters for PPO requires careful tuning and expertise. Balancing exploration (trying new actions) and exploitation (sticking to proven actions) is crucial for PPO's success. Like DQNs, understanding PPO's decision-making process can be challenging.	Deciding the optimal power split between electric motor and engine in real-time based on driving conditions. Anticipating upcoming road events and adjusting powertrain usage accordingly for improved efficiency. Selecting the most efficient driving mode (e.g., hybrid, electric) based on battery state and road characteristics.	[27], [81], [125], [126], [127], [128], [152], [153], [158]

different driving scenarios. This data-driven approach adapts to different driving styles and road conditions, improving performance over time.

Deep Q-Networks (DQNs) are a popular Deep Reinforcement Learning (DRL) technique gaining traction in HEV Energy Management Systems (EMS) [123]. They offer an attractive option for simultaneously optimizing fuel efficiency, emissions, and battery health. DQNs rely on a neural network to estimate the Q-value, which represents the expected future reward of taking a specific action in each state. The agent interacts with the HEV environment (simulator or real vehicle), taking actions based on learned Q-values and receiving rewards/penalties [29]. Over time, the DQN adjusts its internal parameters to maximize future rewards, driving towards optimal control policies.

Beyond established control strategies for HEVs, research delves into three promising areas to enhance DQN performance: reward function design,transfer learning,and integration with other strategies [124]. Crafting effective reward functions that accurately capture desired objectives, like fuel efficiency and smooth driving, is crucial for successful DQN learning.Transfer learning tackles training efficiency by adapting pre-trained DQNs from similar models or driving scenarios, reducing data and time requirements. Finally, integration with other control strategies seeks to leverage the strengths of each approach. Combining DQNs with rule-based algorithms, for example, can benefit from the adaptability of DQNs and the clear-cut rules of traditional methods. Exploring these areas holds significant potential for optimizing DQN-based control in HEVs [29].

Proximal Policy Optimization (PPO) is another powerful Deep Reinforcement Learning (DRL) technique used in HEV Energy Management Systems (EMS) alongside Deep Q-Networks (DQNs). PPO belongs to the policy gradient class of DRL algorithms. Instead of estimating Q-values like DQNs, PPO directly learns a policy, which maps states to actions [125], [126]. In the HEV context, the policy decides how to allocate power between the electric motor and engine in various driving situations. PPO updates the policy through iterations, aiming to maximize the expected cumulative reward (e.g., fuel efficiency). In addition, Tang et al. explored an optimal control-based energy management strategy for HEVs, which balances fuel consumption with battery capacity degradation. The optimal controller integrates a battery aging model, providing valuable insights into the tradeoff between fuel efficiency and battery aging in HEVs. While specific models and results will differ based on battery chemistry and vehicle architecture, the developed models and control algorithms demonstrate the feasibility of considering battery aging in an energy management controller. This approach can significantly extend battery life across various operating conditions with minimal impact on performance and a negligible decrease in fuel economy, [127].

While traditional RL techniques focus on single objectives, recent research is pushing boundaries with Proximal Policy Optimization (PPO). Multi-objective PPO incorporates multiple reward functions to optimize not just fuel efficiency but also crucial considerations like emissions and battery health, leading to a more holistic approach [27]. PPO with off-policy learning leverages past experiences from different driving scenarios, potentially reducing data requirements compared to traditional on-policy approaches. Additionally, combining PPO with other techniques like rule-based systems opens doors for leveraging the adaptability of PPO alongside the clear-cut rules of established methods, potentially leading to further performance improvements. These advanced developments show the promise of PPO in optimizing HEV control for a multitude of objectives [128]. Table 5. compares the benefits and challenges of Deep Q- Networks and Proximal Policy Optimization strategies in HEV.

IV. CHALLENGES AND OPPORTUNITIES

- Different HEV designs have unique limitations. Optimizing size, power demand, and functionality based on specific needs remains an ongoing challenge. Utilizing advanced technologies can boost reliability and efficiency [135], [136].
- Existing EMS solutions often perform well in simulated scenarios but struggle to achieve optimal results in real-time due to dynamic driving conditions [137], [138].
- Global optimization methods offer optimal solutions, but their high computational demands make them impractical for real-time applications. Finding the right balance is crucial [139], [140], [141].
- While fuel efficiency is important, current EMS often neglects other factors like battery health, emissions, and computational complexity. Comprehensive optimization methods considering these factors are needed [139], [142].
- Reducing uncertainty in future driving conditions is key. Integrating information from sources like GIS, ITS, and GPS can provide more accurate traffic data. Additionally, predicting driver behavior and style can further improve efficiency [143], [144], [145].
- Using numerical optimization methods on simplified vehicle models can reduce computational load while maintaining reasonable accuracy [146], [147].
- Considering various performance metrics like battery life, energy savings, emissions, driving style, and drivability in a unified optimization framework presents a promising approach [148], [149].

This review suggests combining RB and optimization methods for a potent blend. It highlights fuzzy logic RB methods as particularly promising due to their ease of implementation, adaptability, and low computational load. However, choosing the right settings for these methods can be tricky. It emphasizes that HEV complexity goes beyond batteries. Sophisticated designs pose additional challenges, such as:

- Choosing the right driving mode: The system needs to dynamically select the most efficient mode based on varying driving conditions.
- Harmonious energy cooperation: Ensuring seamless collaboration between electric and traditional energy sources is crucial for optimal efficiency and reduced emissions.

While methods like Dynamic Programming (DP) offer ideal optimization, their impracticality in real-time applications due to high computational demands and requiring future driving knowledge limits their use. However, DP serves as a valuable benchmark for evaluating other methods and developing guiding principles. This review highlights important trends and open issues in HEV Energy Management Systems (EMS):

- From rule-based to optimization-based methods: Researchers are increasingly focusing on optimization techniques to achieve better performance compared to simpler rule-based approaches [150], [151].
- From predetermined cycles to real-time adaptation: The focus is moving from optimizing for predefined driving cycles to real-time optimization and dynamic control parameter adjustments based on actual driving conditions [152], [153], [154].
- From single objective to multi-objective optimization: Recognizing the need to balance various factors like fuel efficiency, emissions, and battery health, research is shifting towards multi-objective optimization approaches [155], [156].

Crafting better reward functions, leveraging pre-trained models, and integrating with other strategies optimize DQNs for specific goals like fuel efficiency and

smooth driving. Multi-objective PPO tackles emissions, battery health, etc., alongside fuel efficiency. PPO, with off-policy learning, harnesses past experiences for efficient training and combines them with other techniques to leverage their adaptability. These advancements in both DQNs and PPO show promise for optimizing HEV control for diverse objectives.

Lastly, in [159], the author provides a thorough and up-to-date review of energy management systems (EMS) in hybrid electric vehicles (HEVs), 1) Multivariable Output Neural Network Models: These models use artificial neural networks (ANNs) with inverse function mechanisms to simulate fuel consumption in plug-in hybrid electric vehicles (PHEVs). This simulation approach accurately predicts factors such as driving range, battery recharge time, and CO2 emissions across varied driving conditions, offering valuable insights for enhancing fuel economy and energy efficiency in hybrid systems. 2) Cloud-Based Eco-Driving Solutions: This approach, applied in autonomous hybrid buses, uses cooperative vehicle-infrastructure systems combined with dynamic programming to enhance fuel efficiency and driving patterns. Cloud integration allows for real-time data processing and adaptive driving adjustments, which are particularly beneficial for optimizing energy use in urban transit environments.

V. CONCLUSION

This paper explores the intricate world of Energy Management Systems (EMS) in Hybrid Electric Vehicles (HEVs). It examines various strategies and technologies while highlighting key challenges faced in optimizing performance and efficiency. This review contrasts three main approaches: i) Offline EMS plays a crucial role in designing and analyzing HEV control strategies. While they don't handle real-time decision-making, their ability to leverage prior knowledge and computationally intensive algorithms makes them valuable tools for optimizing performance, evaluating online approaches, and generating training data for machine learning. ii) Rule-based methods offer a straightforward way to manage HEV powertrains but often come at the cost of optimality and adaptability. Understanding their advantages and limitations is crucial when designing and implementing HEV control systems. The future of rule-based methods likely lies in hybrid approaches that integrate them with data-driven learning for more intelligent and adaptable control strategies. iii) Optimization-based methods hold immense potential for maximizing HEV performance but require careful consideration of their computational demands, real-time challenges, and dependence on model accuracy. The future lies in continuous advancements, hybrid approaches, and leveraging data-driven techniques to unlock the full potential of these sophisticated EMS strategies.

REFERENCES

[1] Y. Farajpour, H. Chaoui, M. Khayamy, S. Kelouwani, and M. Alzayed, "A hybrid energy management strategy based on ANN and GA optimization for electric vehicles," in *Proc. IEEE Vehicle Power Propuls. Conf. (VPPC)*, Nov. 2022, pp. 1–6.

[2] A. Panday and H. O. Bansal, "Energy management in hybrid electric vehicles using particle swarm optimization method," in *Proc. IEEE 7th Power India Int. Conf. (PIICON)*, Nov. 2016, pp. 1–5.

[3] R. Bejgam, S. Sunkari, S. B. Keshipeddi, M. R. Rangaraju, and V. Dunde, "A brief study on hybrid electric vehicles," in *Proc. 3rd Int. Conf. Inventive Res. Comput. Appl. (ICIRCA)*, I. Coimbatoreth ed. Sep. 2021, pp. 54–59.

[4] A. H. Ganesh and B. Xu, "A review of reinforcement learning based energy management systems for electrified powertrains: Progress, challenge, and potential solution," *Renew. Sustain. Energy Rev.*, vol. 154, Feb. 2022, Art. no. 111833.

[5] Y. Wang and X. Jiao, "Dual heuristic dynamic programming based energy management control for hybrid electric vehicles," *Energies*, vol. 15, no. 9, p. 3235, Apr. 2022.

[6] M. A. Hannan, F. A. Azidin, and A. Mohamed, "Hybrid electric vehicles and their challenges: A review," *Renew. Sustain. Energy Rev.*, vol. 29, pp. 135–150, Jan. 2014.

[7] A. Kleimaier and D. Schroder, "Optimization strategy for design and control of a hybrid vehicle," in *Proc. 6th Int. Workshop Adv. Motion Control*, Apr. 2000, pp. 459–464.

[8] P. Pisu, E. Silani, G. Rizzoni, and S. M. Savaresi, "A LMI-based supervisory robust control for hybrid vehicles," in *Proc. Amer. Control Conf.*, 2003, pp. 4681–4686.

[9] A. Brahma, B. Glenn, Y. Guezennec, T. Miller, G. Rizzoni, and G. Washington, "Modeling, performance analysis and control design of a hybrid sport-utility vehicle," in *Proc. IEEE Int. Conf. Control Appl.*, vol. 1, Aug. 1999, pp. 448–453.

[10] C.-C. Lin, H. Peng, J. W. Grizzle, and J.-M. Kang, "Power management strategy for a parallel hybrid electric truck," *IEEE Trans. Control Syst. Technol.*, vol. 11, no. 6, pp. 839–849, Nov. 2003.

[11] D. Kum, "Modeling and optimal control of parallel HEVs and plug-in HEVs for multiple objectives," Ph.D. dissertation, Dept. Mech. Eng., Univ. Michigan, Ann Arbor, MI, USA, 2010.

[12] H.-D. Lee and S.-K. Sul, "Fuzzy-logic-based torque control strategy for parallel-type hybrid electric vehicle," *IEEE Trans. Ind. Electron.*, vol. 45, no. 4, pp. 625–632, Aug. 1998.

[13] R. Zhang and J. Tao, "GA-based fuzzy energy management system for FC/SC-powered HEV considering H_2 consumption and load variation," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 4, pp. 1833–1843, Aug. 2018.

[14] X. Zeng and J. Wang, "A two-level stochastic approach to optimize the energy management strategy for fixed-route hybrid electric vehicles," *Mechatronics*, vol. 38, pp. 93–102, Sep. 2016.

[15] S. K. Rathor and D. Saxena, "Decentralized energy management system for LV microgrid using stochastic dynamic programming with game theory approach under stochastic environment," *IEEE Trans. Ind. Appl.*, vol. 57, no. 4, pp. 3990–4000, Jul. 2021.

[16] N. Al-Aawar, T. M. Hijazi, and A. A. Arkadan, "Particle swarm optimization of coupled electromechanical systems," *IEEE Trans. Magn.*, vol. 47, no. 5, pp. 1314–1317, May 2011.

[17] K. Ç. Bayindir, M. A. Gözüküçük, and A. Teke, "A comprehensive overview of hybrid electric vehicle: Powertrain configurations, powertrain control techniques and electronic control units," *Energy Convers. Manage.*, vol. 52, no. 2, pp. 1305–1313, Feb. 2011.

[18] S. Hahn, H. Waschl, G. Steinmaurer, and L. del Re, "Extension of a linear optimal control strategy for HEV," in *Proc. Eur. Control Conf. (ECC)*, Jul. 2015, pp. 154–159.

[19] N. Robuschi, M. Salazar, N. Viscera, F. Braghin, and C. H. Onder, "Minimum-fuel energy management of a hybrid electric vehicle via iterative linear programming," *IEEE Trans. Veh. Technol.*, vol. 69, no. 12, pp. 14575–14587, Dec. 2020.

[20] J. F. Franco, M. J. Rider, and R. Romero, "A mixed-integer linear programming model for the electric vehicle charging coordination problem in unbalanced electrical distribution systems," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2200–2210, Sep. 2015.

[21] S. D. Gupta, J. K. Tobin, and L. Pavel, "A two-step linear programming model for energy-efficient timetables in metro railway networks," *Transp. Res. B, Methodol.*, vol. 93, pp. 57–74, Nov. 2016.

[22] C. Bordin, H. O. Anuta, A. Crossland, I. L. Gutierrez, C. J. Dent, and D. Vigo, "A linear programming approach for battery degradation analysis and optimization in offgrid power systems with solar energy integration," *Renew. Energy*, vol. 101, pp. 417–430, Feb. 2017.

[23] G. Cardoso, T. Brouhard, N. DeForest, D. Wang, M. Heleno, and L. Kotzur, "Battery aging in multi-energy microgrid design using mixed integer linear programming," *Appl. Energy*, vol. 231, pp. 1059–1069, Dec. 2018.

[24] L. V. Pérez, G. R. Bossio, D. Moitre, and G. O. García, "Optimization of power management in an hybrid electric vehicle using dynamic programming," *Math. Comput. Simul.*, vol. 73, nos. 1–4, pp. 244–254, Nov. 2006.

[25] Q. Gong, Y. Li, and Z.-R. Peng, "Trip based power management of plug-in hybrid electric vehicle with two-scale dynamic programming," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2007, pp. 12–19.

[26] W. Tang, Y. Wang, X. Jiao, and L. Ren, "Hierarchical energy management strategy based on adaptive dynamic programming for hybrid electric vehicles in car-following scenarios," *Energy*, vol. 265, Feb. 2023, Art. no. 126264.

[27] Z. Zeng, J. Wang, Z. Hu, D. Su, and P. Shang, "Advantage policy update based on proximal policy optimization," *Proc. SPIE*, vol. 12587, pp. 84–90, feb. 2023.
[28] Y. Zhang, Y. Huang, Z. Chen, G. Li, and Y. Liu, "A novel learning-based model predictive control strategy for plug-in hybrid electric vehicle," *IEEE Trans. Transport. Electrific.*, vol. 8, no. 1, pp. 23–35, Mar. 2022.
[29] S. Ahmadian, M. Tahmasbi, and R. Abedi, "Q-learning based control for energy management of series-parallel hybrid vehicles with balanced fuel consumption and battery life," *Energy AI*, vol. 11, Jan. 2023, Art. no. 100217.
[30] D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: An overview," *Soft Comput.*, vol. 22, no. 2, pp. 387–408, Jan. 2018.
[31] J. Sun, C.-H. Lai, and X.-J. Wu, *Particle Swarm Optimisation, Classical and Quantum Perspectives*. Boca Raton, FL, USA: CRC Press, 2016.
[32] N. Al-Aawar, T. M. Hijazi, and A. A. Arkadan, "EM-TFL identification for particle swarm optimization of HEV powertrain," in *Proc. IEEE Int. Electric Mach. Drives Conf.*, May 2009, pp. 109–112.
[33] W. Enang and C. Bannister, "Modelling and control of hybrid electric vehicles (a comprehensive review)," *Renew. Sustain. Energy Rev.*, vol. 74, pp. 1210–1239, Jul. 2017.
[34] A. Panday and H. O. Bansal, "A review of optimal energy management strategies for hybrid electric vehicle," *Int. J. Veh. Technol.*, vol. 2014, pp. 1–19, Nov. 2014.
[35] Y. Song, D. Wu, W. Deng, X.-Z. Gao, T. Li, B. Zhang, and Y. Li, "MPPCEDE: Multi-population parallel co-evolutionary differential evolution for parameter optimization," *Energy Convers. Manage.*, vol. 228, Jan. 2021, Art. no. 113661, doi: 10.1016/j.enconman.2020.113661.
[36] Z. Tan, Y. Tang, K. Li, H. Huang, and S. Luo, "Differential evolution with hybrid parameters and mutation strategies based on reinforcement learning," *Swarm Evol. Comput.*, vol. 75, Dec. 2022, Art. no. 101194, doi: 10.1016/j.swevo.2022.101194.
[37] G. Li, Q. Lin, L. Cui, Z. Du, Z. Liang, J. Chen, N. Lu, and Z. Ming, "A novel hybrid differential evolution algorithm with modified CoDE and JADE," *Appl. Soft Comput.*, vol. 47, pp. 577–599, Oct. 2016, doi: 10.1016/j.asoc.2016.06.011.
[38] R. A. Sarker, S. M. Elsayed, and T. Ray, "Differential evolution with dynamic parameters selection for optimization problems," *IEEE Trans. Evol. Comput.*, vol. 18, no. 5, pp. 689–707, Oct. 2014.
[39] S. Das, S. S. Mullick, and P. N. Suganthan, "Recent advances in differential evolution—An updated survey," *Swarm Evol. Comput.*, vol. 27, pp. 1–30, Apr. 2016.
[40] K. Dev, P. K. R. Maddikunta, T. R. Gadekallu, S. Bhattacharya, P. Hegde, and S. Singh, "Energy optimization for green communication in IoT using Harris hawks optimization," *IEEE Trans. Green Commun. Netw.*, vol. 6, no. 2, pp. 685–694, Jun. 2022.
[41] S. Jafari and Y.-C. Byun, "Optimizing battery RUL prediction of lithium-ion batteries based on Harris hawk optimization approach using random forest and LightGBM," *IEEE Access*, vol. 11, pp. 87034–87046, 2023.
[42] N. Akhter, R. Mahmud, J. Jin, J. But, I. Ahmad, and Y. Xiang, "Configurable Harris hawks optimisation for application placement in space-air-ground integrated networks," *IEEE Trans. Netw. Service Manage.*, vol. 21, no. 2, pp. 1724–1736, Apr. 2024.
[43] N. Kumar, R. Chaudhry, O. Kaiwartya, and N. Kumar, "ChaseMe: A heuristic scheme for electric vehicles mobility management on charging stations in a smart city scenario," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 9, pp. 16048–16058, Sep. 2022.
[44] J. Li, M. Ye, W. Meng, X. Xu, and S. Jiao, "A novel state of charge approach of lithium ion battery using least squares support vector machine," *IEEE Access*, vol. 8, pp. 195398–195410, 2020.
[45] W. Zeng, P. Liu, C. Yang, W. Sun, Y. Huang, and Y. Han, "En-route charging strategy for wirelessly charged electric bus considering time-of-use price," *IEEE Access*, vol. 10, pp. 94063–94073, 2022.
[46] P. Kumar, S. Mukherjee, R. Saini, P. Kaushik, P. P. Roy, and D. P. Dogra, "Multimodal gait recognition with inertial sensor data and video using evolutionary algorithm," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 5, pp. 956–965, May 2019.
[47] Y. Wang, G. Zhao, C. Zhou, M. Li, and Z. Chen, "Lithium-ion battery optimal charging using moth-flame optimization algorithm and fractional-order model," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 4, pp. 4981–4989, Dec. 2023.
[48] B. Long, W. Yang, Q. Hu, J. M. Guerrero, C. Garcia, J. Rodriguez, and K. T. Chong, "Moth–flame-optimization-based parameter estimation for FCS-MPC-controlled grid-connected converter with LCL filter," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 10, no. 4, pp. 4102–4114, Aug. 2022.
[49] M. F. Khan, F. Aadil, M. Maqsood, S. H. R. Bukhari, M. Hussain, and Y. Nam, "Moth flame clustering algorithm for Internet of Vehicle (MFCA-IoV)," *IEEE Access*, vol. 7, pp. 11613–11629, 2019.
[50] Z. E. Liu, Q. Zhou, Y. Li, S. Shuai, and H. Xu, "Safe deep reinforcement learning-based constrained optimal control scheme for HEV energy management," *IEEE Trans. Transp. Electrific.*, vol. 9, no. 3, pp. 4278–4293, Sep. 2023.
[51] M. Ehsani, Y. Gao, S. Long, and K. Ebrahimi, *Modern Electric, Hybrid Electric, and Fuel Cell Vehicles*, 3rd ed., Boca Raton, FL, USA: CRC Press, 2018.
[52] M. E. Hmidi, I. Ben Salem, and L. El Amraoui, "Analysis of rule-based parameterized control strategy for a HEV hybrid electric vehicle," in *Proc. 19th Int. Conf. Sci. Techn. Autom. Control Comput. Eng. (STA)*, Mar. 2019, pp. 112–117.
[53] H. Son, H. Kim, S. Hwang, and H. Kim, "Development of an advanced rule-based control strategy for a PHEV using machine learning," *Energies*, vol. 11, no. 1, p. 89, Jan. 2018.
[54] S. M. Byun, B. S. Kim, and S. W. Cha, "Deterministic rule-based control classification for HEV," *Korean Soc. New Renew. Energy*, vol. 11, p. 1261, Jan. 2006.
[55] M. Sorrentino, G. Rizzo, and I. Arsie, "Analysis of a rule-based control strategy for on-board energy management of series hybrid vehicles," *Control Eng. Pract.*, vol. 19, no. 12, pp. 1433–1441, Dec. 2011.
[56] A. Ahmed and S. Cui, "Different architectures and modes of operation of HEV based on permanent magnet-electric variable transmission with rule-based and fuzzy logic global control strategy," *Int. J. Electric Hybrid Vehicles*, vol. 4, no. 1, pp. 69–92, 2012.
[57] T. A. Anderson, J. M. Barkman, and C. Mi, "Design and optimization of a fuzzy-rule based hybrid electric vehicle controller," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2008, pp. 1–7.
[58] X. Zhang, Y. Liu, J. Zhang, W. Dai, and Z. Liu, "A fuzzy neural network energy management strategy for parallel hybrid electric vehicle," in *Proc. 9th Int. Conf. Modelling, Identificat. Control (ICMIC)*, Kunming, China, 2017, pp. 342–347, doi: 10.1109/ICMIC.2017.8321666.
[59] G.-H. Kim, B.-K. Lee, and J.-H. Kim, "A neuro-fuzzy energy management strategy for hybrid electric vehicles," in *Proc. IEEE Int. Symp. Ind. Electron. (ISIE)*, Jun. 2001, pp. 904–909.
[60] J. Won and R. Langari, "Fuzzy torque distribution control for a parallel hybrid vehicle," *Exp. Syst.*, vol. 19, no. 1, pp. 4–10, Feb. 2002.
[61] O. Kraa, M. Becherif, M. Y. Ayad, R. Saadi, M. Bahri, A. Aboubou, and I. Tegani, "A novel adaptive operation mode based on fuzzy logic control of electrical vehicle," *Energy Proc.*, vol. 50, pp. 194–201, Jan. 2014.
[62] M. Zand, M. A. Nasab, A. Hatami, M. Kargar, and H. R. Chamorro, "Using adaptive fuzzy logic for intelligent energy management in hybrid vehicles," in *Proc. 28th Iranian Conf. Electr. Eng. (ICEE)*, Aug. 2020, pp. 1–7.
[63] O. Turhan, Y. Sayar, B. Hacieyupoglu, H. Batmaz, and C. D. Engin, "Predictive and fuzzy logic controller based P2 HEV energy management strategy benchmark," in *Proc. 14th Int. Conf. Electr. Electron. Eng. (ELECO)*, Dec. 2023, pp. 1–6.
[64] J. J. Justo, F. Mwasilu, E.-K. Kim, J. Kim, H. H. Choi, and J.-W. Jung, "Fuzzy model predictive direct torque control of IPMSMs for electric vehicle applications," *IEEE/ASME Trans. Mechatronics*, vol. 22, no. 4, pp. 1542–1553, Aug. 2017.
[65] K. Kakouche, T. Rekioua, S. Mezani, A. Oubelaid, D. Rekioua, V. Blazek, L. Prokop, S. Misak, M. Bajaj, and S. S. M. Ghoneim, "Model predictive direct torque control and fuzzy logic energy management for multi power source electric vehicles," *Sensors*, vol. 22, no. 15, p. 5669, Jul. 2022.
[66] B. Baumann, G. Rizzoni, and G. Washington, "Intelligent control of hybrid vehicles using neural networks and fuzzy logic," SAE Tech. Paper 981061, 1998, doi: 10.4271/981061.
[67] S. Stockar, V. Marano, M. Canova, G. Rizzoni, and L. Guzzella, "Energy-optimal control of plug-in hybrid electric vehicles for real-world driving cycles," *IEEE Trans. Veh. Technol.*, vol. 60, no. 7, pp. 2949–2962, Sep. 2011, doi: 10.1109/TVT.2011.2158565.
[68] J.-S. Won and R. Langari, "Intelligent energy management agent for a parallel hybrid vehicle—Part II: Torque distribution, charge sustenance strategies, and performance results," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 935–953, May 2005.

[69] R. Langari and J.-S. Won, "Intelligent energy management agent for a parallel hybrid vehicle—Part I: System architecture and design of the driving situation identification process," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 925–934, May 2005.
[70] L. Niu, H. Yang, and Y. Zhang, "Intelligent HEV fuzzy logic control strategy based on identification and prediction of drive cycle and driving trend," *World J. Eng. Technol.*, vol. 3, no. 3, pp. 215–226, 2015.
[71] N. Denis, M. R. Dubois, and A. Desrochers, "Fuzzy-based blended control for the energy management of a parallel plug-in hybrid electric vehicle," *IET Intell. Transp. Syst.*, vol. 9, no. 1, pp. 30–37, Feb. 2015.
[72] M. Mohebbi, M. Charkhgard, and M. Farrokhi, "Optimal neuro-fuzzy control of parallel hybrid electric vehicles," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2005, pp. 26–30.
[73] J. Guo, Z. Guo, C. Liu, and L. Chu, "Adaptive fuzzy control strategy of PHEV based on trip characteristics," in *Proc. 5th Int. Conf. Comput. Sci. Netw. Technol. (ICCSNT)*, 2016, pp. 358–361.
[74] W. Zhou, M. Li, H. Yin, and C. Ma, "An adaptive fuzzy logic based energy management strategy for electric vehicles," in *Proc. IEEE 23rd Int. Symp. Ind. Electron. (ISIE)*, Jun. 2014, pp. 1778–1783.
[75] H. Yin, W. Zhou, M. Li, C. Ma, and C. Zhao, "An adaptive fuzzy logic-based energy management strategy on battery/ultracapacitor hybrid electric vehicles," *IEEE Trans. Transport. Electrific.*, vol. 2, no. 3, pp. 300–311, Sep. 2016.
[76] E. Kamal, L. Adouane, R. Abdrakhmanov, and N. Ouddah, "Hierarchical and adaptive neuro-fuzzy control for intelligent energy management in hybrid electric vehicles," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 3014–3021, Jul. 2017.
[77] P. Li, X. Jiao, and Y. Li, "Adaptive real-time energy management control strategy based on fuzzy inference system for plug-in hybrid electric vehicles," *Control Eng. Pract.*, vol. 107, Feb. 2021, Art. no. 104703.
[78] H. Tian, X. Wang, Z. Lu, Y. Huang, and G. Tian, "Adaptive fuzzy logic energy management strategy based on reasonable SOC reference curve for online control of plug-in hybrid electric city bus," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 5, pp. 1607–1617, May 2018.
[79] S. K. Kakodia and G. Dyanamina, "Type-2 fuzzy logic controller-based stator current model reference adaptive system speed observer for a hybrid electric vehicle to improve transient response during limp home mode," *Int. J. Circuit Theory Appl.*, vol. 50, no. 10, pp. 3426–3442, Oct. 2022.
[80] M. Neuman, H. Sandberg, and B. Wahlberg, "Rule-based control of series HEVs derived from deterministic dynamic programming," in *Automatic Control ACCESS Linnaeus Center*. Stockholm, Sweden: KTH Royal Institute of Technology, 2008.
[81] 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, Apr. 2020, Art. no. 117297.
[82] S. Xie, H. Li, Z. Xin, T. Liu, and L. Wei, "A pontryagin minimum principle-based adaptive equivalent consumption minimum strategy for a plug-in hybrid electric bus on a fixed route," *Energies*, vol. 10, no. 9, p. 1379, Sep. 2017.
[83] N. Kim, S. Cha, and H. Peng, "Optimal control of hybrid electric vehicles based on Pontryagin's minimum principle," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 5, pp. 1279–1287, Sep. 2011.
[84] X. Li, Y. Wang, D. Yang, and Z. Chen, "Adaptive energy management strategy for fuel cell/battery hybrid vehicles using Pontryagin's minimal principle," *J. Power Sources*, vol. 440, Nov. 2019, Art. no. 227105.
[85] G. Paganelli, S. Delprat, T.-M. Guerra, J. Rimaux, and J.-J. Santin, "Equivalent consumption minimization strategy for parallel hybrid powertrains," in *Proc. Veh. Technol. Conf.*, vol. 55, 2002, pp. 2076–2081.
[86] H.-Y. Hwang, "Developing equivalent consumption minimization strategy for advanced hybrid system-II electric vehicles," *Energies*, vol. 13, no. 8, p. 2033, Apr. 2020.
[87] S. Yang, W. Wang, F. Zhang, Y. Hu, and J. Xi, "Driving-style-oriented adaptive equivalent consumption minimization strategies for HEVs," *IEEE Trans. Veh. Technol.*, vol. 67, no. 10, pp. 9249–9261, Oct. 2018.
[88] P. Olin, K. Aggoune, L. Tang, K. Confer, J. Kirwan, S. R. Deshpande, S. Gupta, P. Tulpule, M. Canova, and G. Rizzoni, "Reducing fuel consumption by using information from connected and automated vehicle modules to optimize propulsion system control," *SAE Tech. Paper*, vol. 1213, pp. 2001–2019, Apr. 2019.
[89] F. Qin, G. Xu, Y. Hu, K. Xu, and W. Li, "Stochastic optimal control of parallel hybrid electric vehicles," *Energies*, vol. 10, no. 2, p. 214, Feb. 2017.
[90] G. Ripaccioli, D. Bernardini, S. Di Cairano, A. Bemporad, and I. V. Kolmanovsky, "A stochastic model predictive control approach for series hybrid electric vehicle power management," in *Proc. Amer. Control Conf.*, Jul. 2010, pp. 5844–5849.
[91] B. Liu, L. Li, X. Wang, and S. Cheng, "Hybrid electric vehicle downshifting strategy based on stochastic dynamic programming during regenerative braking process," *IEEE Trans. Veh. Technol.*, vol. 67, no. 6, pp. 4716–4727, Jun. 2018.
[92] Y. Huang, H. Wang, A. Khajepour, H. He, and J. Ji, "Model predictive control power management strategies for HEVs: A review," *J. Power Sources*, vol. 341, pp. 91–106, Feb. 2017.
[93] J. Lian, S. Liu, L. Li, X. Liu, Y. Zhou, F. Yang, and L. Yuan, "A mixed logical dynamical-model predictive control (MLD-MPC) energy management control strategy for plug-in hybrid electric vehicles (PHEVs)," *Energies*, vol. 10, no. 1, p. 74, Jan. 2017.
[94] H. Chen, R. Xiong, C. Lin, and W. Shen, "Model predictive control based real-time energy management for hybrid energy storage system," *CSEE J. Power Energy Syst.*, vol. 7, no. 4, pp. 862–874, Jul. 2021.
[95] H. A. Borhan, C. Zhang, A. Vahidi, A. M. Phillips, M. L. Kuang, and S. Di Cairano, "Nonlinear model predictive control for power-split hybrid electric vehicles," in *Proc. 49th IEEE Conf. Decis. Control (CDC)*, Dec. 2010, pp. 4890–4895.
[96] P. Poramapojana and B. Chen, "Minimizing HEV fuel consumption using model predictive control," in *Proc. IEEE/ASME 8th IEEE/ASME Int. Conf. Mech. Embedded Syst. Appl.*, Jul. 2012, pp. 148–153.
[97] S. Xie, X. Hu, S. Qi, and K. Lang, "An artificial neural network-enhanced energy management strategy for plug-in hybrid electric vehicles," *Energy*, vol. 163, pp. 837–848, Nov. 2018.
[98] B. M. Baumann, "Intelligent control strategies for hybrid vehicles using neural networks and fuzzy logic," Ph.D. dissertation, Dept. Higher Educ., Ohio State Univ., Columbus, OH, USA, 1997.
[99] M. Suzuki, S. Yamaguchi, T. Araki, P. Raksincharoensak, M. Yoshizawa, and M. Nagai, "Fuel economy improvement strategy for light duty hybrid truck based on fuel consumption computational model using neural network," *IFAC Proc. Volumes*, vol. 41, no. 2, pp. 10719–10725, 2008.
[100] H. Li, H. Chaoui, and H. Gualous, "Cost minimization strategy for fuel cell hybrid electric vehicles considering power sources degradation," *IEEE Trans. Veh. Technol.*, vol. 69, no. 11, pp. 12832–12842, Nov. 2020, doi: 10.1109/TVT.2020.3031000.
[101] B.-H. Nguyen, T. Vo-Duy, M. C. Ta, and J. P. F. Trovão, "Optimal energy management of hybrid storage systems using an alternative approach of Pontryagin's minimum principle," *IEEE Trans. Transport. Electrific.*, vol. 7, no. 4, pp. 2224–2237, Dec. 2021.
[102] B.-H. Nguyen, R. German, J. P. F. Trovão, and A. Bouscayrol, "Real-time energy management of battery/supercapacitor electric vehicles based on an adaptation of Pontryagin's minimum principle," *IEEE Trans. Veh. Technol.*, vol. 68, no. 1, pp. 203–212, Jan. 2019.
[103] F. Yi, D. Lu, X. Wang, C. Pan, Y. Tao, J. Zhou, and C. Zhao, "Energy management strategy for hybrid energy storage electric vehicles based on Pontryagin's minimum principle considering battery degradation," *Sustainability*, vol. 14, no. 3, p. 1214, Jan. 2022.
[104] T. Liu, L. Feng, and W. Zhu, "Fuel minimization of a hybrid electric racing car by Quasi-Pontryagin's minimum principle," *IEEE Trans. Veh. Technol.*, vol. 70, no. 6, pp. 5551–5564, Jun. 2021, doi: 10.1109/TVT.2021.3075729.
[105] K. Song, X. Wang, F. Li, M. Sorrentino, and B. Zheng, "Pontryagin's minimum principle-based real-time energy management strategy for fuel cell hybrid electric vehicle considering both fuel economy and power source durability," *Energy*, vol. 205, Aug. 2020, Art. no. 118064.
[106] O. Yazar and S. Coskun, "Equivalent consumption minimization strategy for hybrid electric vehicle with emission assessment," in *Proc. Int. Congr. Human-Comput. Interact., Optim. Robotic Appl. (HORA)*, 2022, pp. 1–6.
[107] Z. Chen, Y. Liu, M. Ye, Y. Zhang, Z. Chen, and G. Li, "A survey on key techniques and development perspectives of equivalent consumption minimisation strategy for hybrid electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 151, Nov. 2021, Art. no. 111607.
[108] H. Zhang, Q. Li, H. Wang, Q. Li, G. Qin, and Q. Wu, "A review of energy management optimization based on the equivalent consumption minimization strategy for fuel cell hybrid power systems," *Fuel Cells*, vol. 22, no. 4, pp. 116–130, Aug. 2022.

[109] H. Marefat, M. Jalalmaab, and N. L. Azad, "Energy management of battery electric vehicles hybridized with supercapacitor using stochastic dynamic programming," in *Proc. SICE Int. Symp. Control Syst.*, Mar. 2018, pp. 199–205.

[110] C. Yang, S. You, W. Wang, L. Li, and C. Xiang, "A stochastic predictive energy management strategy for plug-in hybrid electric vehicles based on fast rolling optimization," *IEEE Trans. Ind. Electron.*, vol. 67, no. 11, pp. 9659–9670, Nov. 2020.

[111] Y. Ma, C. Li, and S. Wang, "Multi-objective energy management strategy for fuel cell hybrid electric vehicle based on stochastic model predictive control," *ISA Trans.*, vol. 131, pp. 178–196, Dec. 2022.

[112] R. Guo, X. Xue, Z. Sun, and Z. Hong, "Clustered energy management strategy of plug-in hybrid electric logistics vehicle based on Gaussian mixture model and stochastic dynamic programming," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 2, pp. 3177–3191, Jun. 2023.

[113] F. Yan, J. Wang, and K. Huang, "Hybrid electric vehicle model predictive control torque-split strategy incorporating engine transient characteristics," *IEEE Trans. Veh. Technol.*, vol. 61, no. 6, pp. 2458–2467, Jul. 2012.

[114] R. Rodriguez, J. P. F. Trovão, and J. Solano, "Fuzzy logic-model predictive control energy management strategy for a dual-mode locomotive," *Energy Convers. Manage.*, vol. 253, Feb. 2022, Art. no. 115111.

[115] H. Borhan and A. Vahidi, "Model predictive control of a hybrid electric powertrain with combined battery and ultracapacitor energy storage system," *Int. J. Powertrains*, vol. 1, no. 4, pp. 351–376, 2012.

[116] H. Ali Borhan and A. Vahidi, "Model predictive control of a power-split hybrid electric vehicle with combined battery and ultracapacitor energy storage," in *Proc. Amer. Control Conf.*, Jul. 2010, pp. 5031–5036.

[117] M. J. Esfandyari, M. R. Hairi Yazdi, V. Esfahanian, M. Masih-Tehrani, H. Nehzati, and O. Shekoofa, "A hybrid model predictive and fuzzy logic based control method for state of power estimation of series-connected lithium-ion batteries in HEVs," *J. Energy Storage*, vol. 24, Aug. 2019, Art. no. 100758.

[118] A. Vogel, D. Ramachandran, R. Gupta, and A. Raux, "Improving hybrid vehicle fuel efficiency using inverse reinforcement learning," in *Proc. AAAI Conf. Artif. Intell.*, 2012, vol. 26, no. 1, pp. 384–390.

[119] Z. Chen, Y. Liu, Y. Zhang, Z. Lei, Z. Chen, and G. Li, "A neural network-based ECMS for optimized energy management of plug-in hybrid electric vehicles," *Energy*, vol. 243, Mar. 2022, Art. no. 122727.

[120] F. Millo, L. Rolando, L. Tresca, and L. Pulvirenti, "Development of a neural network-based energy management system for a plug-in hybrid electric vehicle," *Transp. Eng.*, vol. 11, Mar. 2023, Art. no. 100156.

[121] J. Hong, Z. Wang, W. Chen, L.-Y. Wang, and C. Qu, "Online joint-prediction of multi-forward-step battery SOC using LSTM neural networks and multiple linear regression for real-world electric vehicles," *J. Energy Storage*, vol. 30, Aug. 2020, Art. no. 101459.

[122] Q. H. Vuong, Y. Zhang, and K. W. Ross, "Supervised policy update for deep reinforcement learning," in *Proc. Int. Conf. Learn. Represent.*, 2018, pp. 1–21.

[123] J. Tao, R. Zhang, Z. Qiao, and L. Ma, "Q-learning-based fuzzy energy management for fuel cell/supercapacitor HEV," *Trans. Inst. Meas. Control*, vol. 44, no. 10, pp. 1939–1949, Jun. 2022.

[124] J. Zhou, S. Xue, Y. Xue, Y. Liao, J. Liu, and W. Zhao, "A novel energy management strategy of hybrid electric vehicle via an improved TD3 deep reinforcement learning," *Energy*, vol. 224, Jun. 2021, Art. no. 120118.

[125] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," 2017, *arXiv:1707.06347*.

[126] W. Zhu and A. Rosendo, "Proximal policy optimization smoothed algorithm," 2020, *arXiv:2012.02439*.

[127] L. Tang, G. Rizzoni, and S. Onori, "Energy management strategy for HEVs including battery life optimization," *IEEE Trans. Transport. Electrific.*, vol. 1, no. 3, pp. 211–222, Oct. 2015.

[128] C. Zhang, T. Li, W. Cui, and N. Cui, "Proximal policy optimization based intelligent energy management for plug-in hybrid electric bus considering battery thermal characteristic," *World Electric Vehicle J.*, vol. 14, no. 2, p. 47, Feb. 2023.

[129] Y. Hu, W. Li, K. Xu, T. Zahid, F. Qin, and C. Li, "Energy management strategy for a hybrid electric vehicle based on deep reinforcement learning," *Appl. Sci.*, vol. 8, no. 2, p. 187, Jan. 2018.

[130] X. Tang, J. Chen, T. Liu, Y. Qin, and D. Cao, "Distributed deep reinforcement learning-based energy and emission management strategy for hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 70, no. 10, pp. 9922–9934, Oct. 2021.

[131] Z. Wang, H. He, J. Peng, W. Chen, C. Wu, Y. Fan, and J. Zhou, "A comparative study of deep reinforcement learning based energy management strategy for hybrid electric vehicle," *Energy Convers. Manage.*, vol. 293, Oct. 2023, Art. no. 117442.

[132] X. Tang, J. Chen, H. Pu, T. Liu, and A. Khajepour, "Double deep reinforcement learning-based energy management for a parallel hybrid electric vehicle with engine start–stop strategy," *IEEE Trans. Transport. Electrific.*, vol. 8, no. 1, pp. 1376–1388, Mar. 2022.

[133] N. Cui, W. Cui, and Y. Shi, "Deep reinforcement learning based PHEV energy management with co-recognition for traffic condition and driving style," *IEEE Trans. Intell. Vehicles*, vol. 8, no. 4, pp. 3026–3039, Apr. 2024.

[134] P. Maroto Estrada, D. de Lima, P. H. Bauer, M. Mammetti, and J. C. Bruno, "Deep learning in the development of energy management strategies of hybrid electric vehicles: A hybrid modeling approach," *Appl. Energy*, vol. 329, Jan. 2023, Art. no. 120231.

[135] H. Borhan, A. Vahidi, A. M. Phillips, M. L. Kuang, I. V. Kolmanovsky, and S. Di Cairano, "MPC-based energy management of a power-split hybrid electric vehicle," *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 3, pp. 593–603, May 2012.

[136] J. Gu, H. Wang, G. Ding, Y. Xu, Z. Xue, and H. Zhou, "Energy-constrained completion time minimization in UAV-enabled Internet of Things," *IEEE Internet Things J.*, vol. 7, no. 6, pp. 5491–5503, Jun. 2020.

[137] R. Koubaa and L. Krichen, "Double layer metaheuristic based energy management strategy for a fuel cell/ultra-capacitor hybrid electric vehicle," *Energy*, vol. 133, pp. 1079–1093, Aug. 2017.

[138] F. Herrmann and F. Rothfuss, "Introduction to hybrid electric vehicles, battery electric vehicles, and off-road electric vehicles," in *Advances in Battery Technologies for Electric Vehicles*. Sawston, U.K.: Woodhead Publishing, 2015, pp. 3–16.

[139] F. Zhang, L. Wang, S. Coskun, H. Pang, Y. Cui, and J. Xi, "Energy management strategies for hybrid electric vehicles: Review, classification, comparison, and outlook," *Energies*, vol. 13, no. 13, p. 3352, Jun. 2020.

[140] S. Najjaran, Z. Rahmani, and M. Hassanzadeh, "Fuzzy predictive control strategy for plug-in hybrid electric vehicles over multiple driving cycles," *Int. J. Dyn. Control*, vol. 10, no. 3, pp. 930–941, Jun. 2022.

[141] Q. Xue, X. Zhang, T. Teng, J. Zhang, Z. Feng, and Q. Lv, "A comprehensive review on classification, energy management strategy, and control algorithm for hybrid electric vehicles," *Energies*, vol. 13, no. 20, p. 5355, Oct. 2020.

[142] S. Hussain, M. U. Ali, G.-S. Park, S. H. Nengroo, M. A. Khan, and H.-J. Kim, "A real-time bi-adaptive controller-based energy management system for battery-supercapacitor hybrid electric vehicles," *Energies*, vol. 12, p. 4662, Dec. 2019.

[143] 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," *Renew. Sustain. Energy Rev.*, vol. 151, Nov. 2021, Art. no. 111521, doi: 10.1016/j.rser.2021.111521.

[144] A. Hajizadeh and M. A. Golkar, "Intelligent power management strategy of hybrid distributed generation system," *Int. J. Electr. Power Energy Syst.*, vol. 29, no. 10, pp. 783–795, Dec. 2007.

[145] J. Pavlovic, A. Marotta, and B. Ciuffo, "CO_2 emissions and energy demands of vehicles tested under the NEDC and the new WLTP type approval test procedures," *Appl. Energy*, vol. 177, pp. 661–670, Sep. 2016.

[146] B. Duan, Q. Wang, X. Zeng, Y. Gong, D. Song, and J. Wang, "Calibration methodology for energy management system of a plug-in hybrid electric vehicle," *Energy Convers. Manage.*, vol. 136, pp. 240–248, Mar. 2017.

[147] K. Ettihir, M. Higuita Cano, L. Boulon, and K. Agbossou, "Design of an adaptive EMS for fuel cell vehicles," *Int. J. Hydrogen Energy*, vol. 42, no. 2, pp. 1481–1489, Jan. 2017.

[148] H. Lee, C. Song, N. Kim, and S. W. Cha, "Comparative analysis of energy management strategies for HEV: Dynamic programming and reinforcement learning," *IEEE Access*, vol. 8, pp. 67112–67123, 2020.

[149] D. Chrenko, S. Gan, C. Gutenkunst, R. Kriesten, and L. Le Moyne, "Novel classification of control strategies for hybrid electric vehicles," in *Proc. IEEE Vehicle Power Propuls. Conf. (VPPC)*, Oct. 2015, pp. 1–6.

[150] M. F. Mohd Sabri, K. A. Danapalasingam, and M. F. Rahmat, "Improved fuel economy of through-the-road hybrid electric vehicle with fuzzy logic-based energy management strategy," *Int. J. Fuzzy Syst.*, vol. 20, no. 8, pp. 2677–2692, Dec. 2018.

[151] K. V. Vidyanandan, "Overview of electric and hybrid vehicles," *Energy Scan.*, vol. 3, pp. 7–14, Mar. 2018.

[152] S. G. Wirasingha and A. Emadi, "Classification and review of control strategies for plug-in hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 60, no. 1, pp. 111–122, Jan. 2011.
[153] C. Zheng, D. Zhang, Y. Xiao, and W. Li, "Reinforcement learning-based energy management strategies of fuel cell hybrid vehicles with multi-objective control," *J. Power Sources*, vol. 543, Sep. 2022, Art. no. 231841.
[154] R. Han, R. Lian, H. He, and X. Han, "Continuous reinforcement learning-based energy management strategy for hybrid electric-tracked vehicles," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 11, no. 1, pp. 19–31, Feb. 2023.
[155] N. Bizon, "Real-time optimization strategies of fuel cell hybrid power systems based on load-following control: A new strategy, and a comparative study of topologies and fuel economy obtained," *Appl. Energy*, vol. 241, pp. 444–460, May 2019.
[156] F. Rajaei Salmasi, "Control strategies for hybrid electric vehicles: Evolution, classification, comparison, and future trends," *IEEE Trans. Veh. Technol.*, vol. 56, no. 5, pp. 2393–2404, Sep. 2007.
[157] B. Xu, X. Tang, X. Hu, X. Lin, H. Li, D. Rathod, and Z. Wang, "Q-learning-based supervisory control adaptability investigation for hybrid electric vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 7, pp. 6797–6806, Jul. 2022.
[158] M. Ehsani, Y. Gao, and J. M. Miller, "Hybrid electric vehicles: Architecture and motor drives," *Proc. IEEE*, vol. 95, no. 4, pp. 719–728, Apr. 2007.
[159] B. P. Adedeji, "A multivariable output neural network approach for simulation of plug-in hybrid electric vehicle fuel consumption," *Green Energy Intell. Transp.*, vol. 2, no. 2, Apr. 2023, Art. no. 100070.

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