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Energy Management Strategy Based on Rules in PHEV: A Review

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Abstract. Electric vehicles (EVs) are gaining increasing attention due to their environmental friendliness. However, EVs still suffer from issues such as short driving range. Plug-in Hybrid Vehicles (PHEVs) have emerged as an intermediate step in the transition from fuel-powered vehicles to electric vehicles, utilizing both gasoline and batteries. The proper allocation of these two energy sources has become a key issue for PHEVs. This paper mainly summarizes and analyzes rule-based energy management strategies through literature analysis, case analysis, and review methods. By contrasting with the energy management based on optimization algorithm, the advantages and problems of rule-based energy management strategies are explored. This paper finds that rule-based energy management strategies offer advantages such as robustness, simple algorithms, and strong real-time performance, but they cannot achieve global optimization, and rule formulation relies heavily on the designer's experience. In addition, rule-based energy management strategies can be combined with multiple algorithms and have high improvement potential.

Keywords: PHEV, rule-based, fuzzy rules

1. Introduction

As environmental protection is gaining increasing attention, the automotive industry is also moving towards more environmentally friendly approaches, leading to an increasing adoption of electric propulsion in vehicles. However, pure electric vehicles still face issues such as insufficient power reserves. Therefore, PHEVs have emerged as a transitional vehicle from traditional vehicles to EVs. While these vehicles utilize both Internal Combustion Engine (ICE) and Electric Motor (EM) as power sources, how to allocate electricity and fuel energy for more efficient use has become the key issue for PHEVs.

The rule-based energy management strategy manages to achieve overall energy utilization efficiency while reducing the emission of polluting gases. This kind of strategy is widely used nowadays with the development of PHEV and EM [1]. Rule-based energy management strategies can be divided into two categories: energy management strategies based on deterministic rules and energy management strategies based on fuzzy rules [2].

This paper summarizes and categorizes existing literature, provides a general overview of rule-based energy management strategies, and respectively further refines and categorizes two kinds of

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management strategies based on rules according to the determinants of the rules and the number of Fuzzy Logic Controllers (FLCs). Rule-based energy management strategies will be compared with strategies based on optimization algorithms to explain the advantages and disadvantages of rule-based energy management strategies. Rule-based strategies are currently popular in practical applications. This article summarizes and organizes information to facilitate future development and application, and also provides an outlook on the future energy development trend of rule-based PHEVs.

2. Energy management strategy based on deterministic rules

Deterministic rule-based energy management controls the power system according to well-defined rules. A reasonable set of mode transition parameters is set to limit the increase or decrease in the power source's output power, effectively achieving mode transitions based on fixed thresholds. Timely mode transitions ensure that the power source remains within a high efficiency range under varying conditions.

2.1. Management strategy based on State of Charge (SOC)

While electric propulsion offers advantages such as enhanced environmental friendliness and higher energy efficiency, it also faces challenges related to limited battery capacity. For short-distance driving, the primary strategy is to rely on electric power. For extended journeys, a hybrid approach combining gasoline and electric propulsion is typically adopted. As a result, the State of Charge (SOC) has become a critical parameter in determining mode transitions in Plug-in Hybrid Electric Vehicles (PHEVs). The decision to switch between operating modes is based on whether the vehicle’s SOC reaches an empirically predefined threshold.

Operating modes can be roughly categorized into Charge-Depleting (CD) mode and Charge-Sustaining (CS) modes, depending on whether the battery is depleted [3]. In CD mode, the powertrain prioritizes the use of the EM. The ICE only works when the electric motor cannot meet power demands. In CS mode, the ICE offers the majority of power, with the EM operating only for auxiliary driving or regenerative braking. When the SOC exceeds a set threshold, the vehicle uses CD mode, while when the SOC is below the threshold, the vehicle uses CS mode. This ensures that the electric motor operates when the SOC is close to the set threshold, preventing excessive energy loss due to a low battery.

2.2. Management strategies determined by multiple parameters

Unlike management strategies that rely solely on SOC, multi-parameter management strategies utilize multiple operating parameters and steady-state efficiency maps of key components to determine the vehicle's operating state. Common operating parameters include SOC, vehicle speed, drivetrain torque demand, driver power demand, and brake pedal position [4]. Because these strategies consider a more comprehensive set of parameters than SOC-based management strategies, multi-parameter management strategies can further refine power distribution.

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Table 1. The working conditions of EM and ICE in different operating modes

Operating modes	The ratio of EM propulsion	The ratio of ICE propulsion
EV	High	\
BHEV	Medium	Medium
CHEV	Medium	High
ENG	\	High
ENC	Charging	High
REG	Charging	\

As it is shown in Table 1, based on the ratio of EM to ICE propulsion, the powertrain can be categorized into the following operating modes: Electric Vehicle mode (EV), Both Hybrid Electric Vehicle mode (BHEV), Combined Hybrid Electric Vehicle mode (CHEV), Engine mode (ENG), Engine Charging mode (ENC), and Regenerative braking mode (REG). The proportion of each power source can be adjusted based on various parameter settings, enabling timely switching between various operating modes. More modes enable automobiles to keep the engine and motor in a smaller range with higher efficiency when facing various conditions, and recuperate energy through the REG mode, which makes the automobiles even more efficient.

2.3. Optimization strategy for deterministic rules

Deterministic rules offer advantages such as fast computation, ease of deployment on real vehicles, clear logic, explicit mode switching, and suitability for most driving scenarios. However, due to their fixed thresholds, they can be inadequate for complex road conditions and changes in vehicle status. Therefore, consideration is being given to integrating Dynamic Programming (DP) into deterministic rules for optimization [5]. With the predictive knowledge offered by a Worldwide Light-duty vehicles Test Cycle (WLTC), DP calculates the optimal energy allocation sequence for the overall situation. By deeply analyzing the behavioral patterns of this optimal solution, it extracts implicit, improved control rules. These new rules can then be used to improve the original empirically based rule-based strategy.

While the DP algorithm can find the optimal strategy for the overall situation, it requires predictive knowledge of the whole road conditions and frequent mode switching, placing higher demands on the vehicle's information acquisition capabilities and component durability. Therefore, based on DP, Shi et al. proposed an improved rule-based strategy (IRB) [4]. This strategy requires a linear decrease in SOC with driving distance, while also controlling the SOC using upper and lower limits to avoid frequent mode switching. With a linear decrease in SOC, the referenced SOC can be expressed as [4]:

$$SOC_r = SOC_0 - \frac{SOC_0 - SOC_{min}}{D_{totel}} \times D_{current} \quad (1)$$

In the formula, SOC_r is the referenced SOC, SOC_0 is initial SOC, SOC_{min} is the minimum SOC, D_{totel} is the total distance traveled and $D_{current}$ is current distance traveled.

Therefore, IRB only requires predictive knowledge of the total driving distance to achieve global optimization of the deterministic rule.

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3. Energy management strategy based on fuzzy rules

Fuzzy rules were developed to compensate for the rigidity of deterministic rules. Fuzzy rule algorithms simplify complex problems by fuzzifying them. They also incorporate fuzzy set theory, allowing a state to partially belong to a category. Specifically, energy management strategies based on fuzzy rules do not rely on fixed values. Instead, they use a specific fuzzification algorithm to convert data into satisfaction indicators, and then use fuzzy rules to determine system outputs.

3.1. Fuzzy rule algorithm

Fuzzy rule algorithms process uncertainty and fuzzy information by simulating human approximate reasoning. The basic idea is to use fuzzy rules and fuzzy reasoning processes to obtain fuzzy or clear output from input.

Here are the main components of the fuzzy rule algorithm(see Table 2):

Table 2. The main part of the fuzzy rule algorithm

Fuzzy Rules	The common form is IF (fuzzy condition) THEN (fuzzy conclusion)
Fuzzification	Converting the clear input value into the membership degree of the corresponding fuzzy set.
Inference Engine	The trigger strength of each rule is calculated using fuzzy operators. The conclusion part is cropped or scaled according to the trigger strength to generate the fuzzy output.
Aggregation	Combine the fuzzy outputs of all rules into a total fuzzy output set.
Defuzzification	Convert aggregated fuzzy output to crisp numeric values by using certain algorithm.

The fuzzy logic controller can fuzzify the input information according to a specific membership function, convert it into a degree of membership, and obtain fuzzy conclusions through fuzzy rules [6]. The inference engine then processes the conclusions based on the degree of triggering of the rules to generate fuzzy outputs. The fuzzy outputs are aggregated and the output set is defuzzified using a specific algorithm to obtain clear values after complete processing by the fuzzy algorithm.

3.2. Strategies using a single FLC

For a single FLC, several items of data are simultaneously received at the input, such as SOC, engine torque difference (ΔT), and current motor speed (Nm) [7]. Since only one fuzzy controller manages energy distribution, the output is often power-related data such as the target torque of the two power sources and the engine torque coefficient K, which directly controls the working state of the motor and engine. The strategy of using a single FLC has a single unified rule base and reasoning mechanism, and the rules are coordinated and consistent.

For example, the fuzzy logic control strategy developed by Zhang et al. for parallel PHEVs uses the powertrain torque demand, T_{req}, and the SOC as inputs, while the desired output is the engine torque demand, T_{out} [8]. The inputs are fuzzified using Triangular Membership Function to obtain fuzzy subsets, and the fuzzy subsets for the outputs and fuzzy rules are also defined. The specific fuzzy rules are shown in Table 3:

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Table 3. The fuzzy rules table

SOC/T_{req}	VS	SE	S	M	B	BE	VB
very low	M	M	B	BE	VB	VB	VB
lower	S	M	B	BE	BE	VB	VB
low	S	M	B	B	BE	BE	BE
normal	SE	S	M	M	B	BE	BE
high	SE	S	M	M	M	B	B
higher	VS	SE	S	M	M	M	M
very high	VS	VS	SE	S	M	M	M

According to the rule table, fuzzy inputs can be converted to fuzzy outputs. Mamdani Fuzzy Inference and Centroid Defuzzification are then used to determine the precise engine torque output.

This example illustrates that a control system using a single FLC has only one core module. Initially, managing the rule base and membership functions is relatively straightforward, with a simple structure and easy initial implementation. However, as the number of input variables increases, the number of fuzzy rules grows exponentially, making the rule base extremely cumbersome and difficult to design, debug, and maintain. Furthermore, to accommodate all situations, the strategy of using a single FLC must make compromises, limiting control accuracy and adaptability, and preventing in-depth optimization for specific subtasks.

3.3. Strategies using multiple fuzzy logic controllers

To address the exponential growth in the number of rules caused by multiple input variables, it is possible to consider using multiple FLCs to form a control system. Using a hierarchical or parallel structure, complex control tasks can be broken down into multiple subtasks, each handled by a dedicated fuzzy logic controller. Each controller only needs to process a subset of the relevant input variables. Li et al. constructed a control system for series HPEVs using three fuzzy logic controllers, employing both hierarchical and parallel structures [9]. The three controllers are the battery working state (BWS) Fuzzy Calculator, FLC1, and FLC2. The specific structure of the control system is shown in Figure 1:

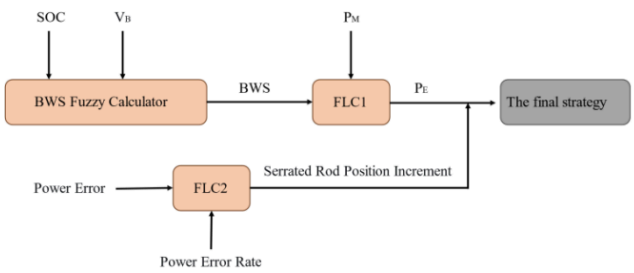

Figure 1. The structure of the control system

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Dedicated controllers within a control system composed of multiple fuzzy logic controllers can achieve more refined and optimized control within their specific areas of responsibility. Through functional decomposition, each controller only needs to process a subset of relevant input variables, reducing the number of rules from a product relationship to a sum relationship, greatly simplifying the design. However, due to the relatively complex structure of the control system, while each sub-controller is simpler to design, the number of controllers that need to be designed and calibrated increases. Furthermore, it is necessary to ensure optimal collaboration between modules. If the interfaces between modules are not properly designed, a small error in one module can propagate and amplify throughout the system, affecting overall performance. This places high demands on control system designers.

4. Conclusion

Energy management strategies based on rules offer advantages such as strong robustness, simple algorithms and strong real-time performance. However, these strategies are less adaptable to complex situations and lack precise energy allocation. The strategies can only ensure the power source operates within a relatively high efficiency range through mode switching, but cannot guarantee that the power source always operates at its highest efficiency, leaving a significant gap between the theoretical efficiency ceiling. Furthermore, these rules are based solely on the designer's experience and fail to maximize the PHEV's fuel-saving potential.

Because the energy management strategies involved in this article utilize different vehicle structures, powertrains, and other key parameters for testing or simulation, and the rules set by the designers are not exactly the same, it has limited meaning to directly compare the efficiency improvement capabilities of each strategy in different vehicle models. If a unified vehicle model can be established to simulate each strategy separately, more specific and direct results can be obtained.

Optimizing rules requires external road information as a supplement. With the development of intelligent control algorithms and connected vehicle technologies, the introduction of more predictive knowledge, combined with optimization methods such as dynamic programming (DP), will improve the adaptability and global optimality of strategies while maintaining real-time performance.

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