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Review article: A comprehensive review of energy management strategies for hybrid electric vehicles

Yuzheng Zhu, Xueyuan Li, Qi Liu, Songhao Li, and Yao Xu

School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China

Correspondence: Xueyuan Li (lixueyuan@bit.edu.cn)

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Abstract. In order to prevent the aggravation of global environmental problems, all industries are facing the challenge of green development. In the automotive field, the development of "new-energy vehicles" (plug-in electric vehicles) is particularly necessary. Hybrid electric vehicles (HEVs) have been proven to be an efficient way of solving environmental and energy problems. As the core of HEVs, the energy management strategy (EMS) plays an important role in fuel economy, power performance, and drivability. However, considering the randomness of actual driving conditions, there are great challenges involved in the establishment of an EMS. Therefore, it is critical to develop an efficient and adaptable EMS. This paper presents a systematic review of EMSs for HEVs. First, different issues that can affect the performance of EMSs are summarized. Second, recent studies on EMSs for HEVs are reviewed. Third, the advantages and disadvantages of different categories of EMSs are compared in detail. Finally, promising EMS research topics for future study are put forward.

1 Introduction

In the world today, the greenhouse effect is becoming more and more serious, and the global energy crisis is intensifying. In addition, the quantity of vehicles is increasing year by year. Because of the severe situation, governments around the world have published policies for the development of "new-energy vehicles" (plug-in electric vehicles) to promote the transformation and development of the traditional automobile industry. Under the current industrial conditions, hybrid electric vehicles (HEVs) have become one of the most important divisions of new-energy vehicles with respect to solving energy and environmental problems. Compared with electric vehicles (EVs), HEVs can get rid of the limitations of battery technology, improve endurance with lower energy consumption and emissions, realize the complementary advantages of multiple power sources, and improve the integral performance of the vehicle.

A HEV is a nonlinear, multi-input, multivariable complex system with two or more power sources. One power source is a traditional internal combustion engine (ICE), and the other power source is a fuel cell, generator, electric motor (EM), or other components (Miller, 2010). One or more power sources provide the demand power for HEVs according to different working conditions. A HEV includes the mutual conversion process of electrical energy, mechanical energy, and internal energy (Xue et al., 2020). In general, HEVs can be divided into series, parallel, and power-split types (Sabri et al., 2016). In series-type HEVs, the ICE does not directly drive the vehicle but instead provides energy to the EM and the battery through the ICE generator. This structure has fewer driving modes, and there is no dynamic coupling problem between various power sources, so the control process is relatively simple (Miller, 2006). For the parallel-type and power-split-type HEVs, multiple power sources can be driven individually or jointly according to the working conditions (Singh et al., 2019). A coupling mechanism between the power sources is applied to realize the power output under different working conditions, so the control process is more complicated (Husain 2005). The coupling mechanism can be divided into a torque-coupling type, a speed-coupling type, and a power-coupling type (Krithika and Subramani, 2018). It can be adopted to adjust and optimize the working state of each power source, thereby improving the performance of the vehicle (Xiang et al., 2010).

As the core technology of HEVs, the energy management strategy (EMS) directly affects the economy, power perfor-

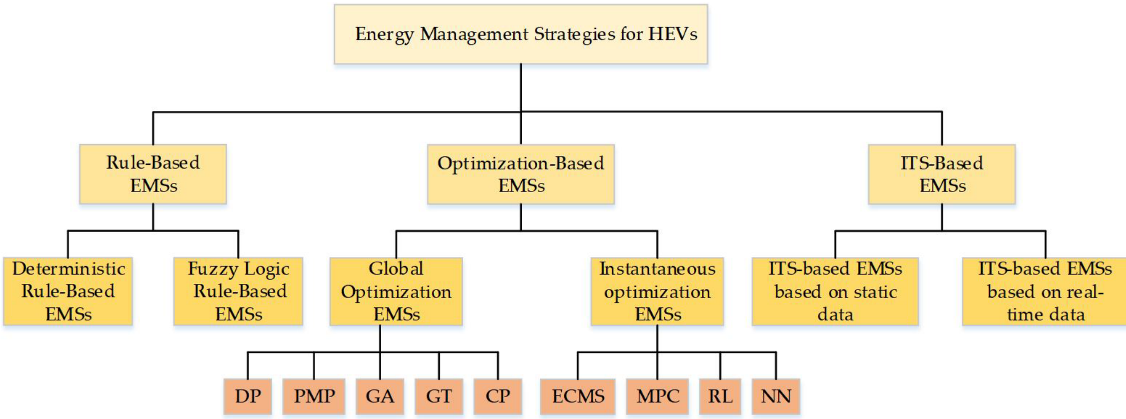

Figure 1. Types of energy management strategies (EMSs) for hybrid electric vehicles (HEVs). Please see Appendix A for a full list of the abbreviations used in the figures.

mance, driving performance, and reliability of the vehicle. The EMS solves the problem of energy distribution between different power sources (Wang et al., 2017a; Hannan et al., 2014). According to the state of charge (SOC), the driver's pedal signal, the characteristics of the ICE and the EM, and the power demand of the vehicle, the power or torque distribution of each power source is solved to improve the fuel economy of the vehicle (Sulaiman et al., 2015; Zhao and Guo, 2016).

In recent years, as the level of research has increased, various EMSs have been developed and have gradually matured (Panday and Bansal, 2014). At first, scholars developed rule-based EMSs based on experience. Following this, global optimization EMSs, based on dynamic programming (DP) and Pontryagin's minimum principle (PMP), and instantaneous optimization EMSs, based on the equivalent consumption minimization strategy (ECMS) and model predictive control (MPC), were successively proposed. With the emergence of various intelligent algorithms and the continuous progress of EMSs, genetic algorithm (GA), game theory (GT), convex optimization (CO), reinforcement learning (RL), and neural networks (NNs) have been gradually applied in EMSs. In addition, with the continuous development of the intelligent transportation system (ITS) and "Internet of Vehicles" (IoV) technology, the information interaction between vehicles, roads, and people has gradually deepened. Information based on the ITS has also been gradually applied to EMSs, as it extends the energy management issue from a vehicle to the transportation system. With the development of HEV technology, the existing EMSs have been updated and optimized, and EMSs based on multi-method fusion are continuously proposed. The performance of EMSs is continuously being improved, and multiple efficient EMSs are gradually being applied to HEVs. The specific types of EMSs for HEVs are shown in Fig. 1 (F. Zhang et al., 2020). Many scholars have conducted extensive and in-depth research on HEV energy management, and many representative review articles have been published that comprehensively summarize EMSs and can be used as guidance.

The characteristics of the different reviews are summarized in Table 1.

With the development and application of the ITS, EMSs of HEVs are gradually separated from the limitation of one vehicle and are oriented toward optimization based on the whole traffic system. Therefore, on the basis of traditional classification methods, EMSs are divided into rule-based, optimization-based, and ITS-based strategies. This paper is organized as follows: in Sect. 2, limitations of HEV driving conditions and the issues considered in EMSs are summarized; in Sects. 3–5, the research status of rule-based EMSs, optimization-based EMSs, and ITS-based EMSs is reviewed in detail; finally, in Sect. 6, promising EMS research topics for future study are briefly put forward.

2 Research on energy management issues

Energy management is a key issue in the research of HEVs and is fundamental for the efficient and clean operation of the vehicles. Energy management aims to solve the problem of energy distribution among different HEV power sources. Based on different HEV driving conditions, the output of each power source is reasonably distributed to meet the driving demands of HEVs; the performance demands of the vehicle economy, emissions, and other aspects; and to extend the service life in the meantime (Martínez et al., 2017; Yu et al., 2006). During actual driving, HEVs are divided into different working conditions according to the working state of the ICE and the EM. Under different working conditions, the power demand of each component is quite different (F. Zhang et al., 2019); therefore, the role of the EMS is to fully exploit the respective advantages of the ICE and the EM so that most of

Table 1. Summary of exemplary works reviewing energy management strategies (EMSs).

Reference	Characteristics
Panday and Bansal (2014)	– Concentrates on battery-powered hybrid vehicles – EMSs are divided into rule-based and optimization-based strategies
Zhao and Guo (2016)	– Describes energy management issues – EMSs are divided into rule-based and optimization-based strategies
Wang et al. (2017a)	– Concentrates on plug-in hybrid electric vehicles – Describes energy management issues – EMSs based on different algorithms are presented in parallel
Krithika and Subramani (2018)	– Concentrates on various architectures of HEVs and different methodologies – Describes design criteria and optimization techniques for the driving cycle – Describes different electric propulsion systems and control strategies
Xue et al. (2020)	– Concentrates on the classification method and multilevel classification of HEVs – Describes the principle and research status of EMSs for each type of HEV – Compares and analyzes the EMSs of HEVs with respect to their characteristics
F. Zhang et al. (2020)	– Concentrates on the power train topologies of HEVs – EMSs are divided into online EMSs and off-line EMSs – Describes the driving cycle prediction approach

the working parts can operate in the high-efficiency range in order to improve the efficiency of the vehicle.

The energy management issues not only take the working range and emissions of the ICE into account but also the efficiency of the EM, the battery, and the transmission system. In the process of energy management, modeling and optimization should be carried out according to one or more optimization objectives (Hannan et al., 2014). Irrespective of the kind of EMS adopted, in addition to meeting the vehicle driving demands, it needs to meet the safety performance demands. Therefore, the implementation of the EMS needs to meet the following boundary conditions:

$$\begin{cases} T_{\mathrm{e_{min}}} \leq T_{\mathrm{e}} \leq T_{\mathrm{e_{max}}} \\ \omega_{\mathrm{e\_min}} \leq \omega_{\mathrm{e}} \leq \omega_{\mathrm{e_{max}}} \\ T_{\mathrm{m_{min}}} \leq T_{\mathrm{m}} \leq T_{\mathrm{m_{max}}} \\ \omega_{\mathrm{m_{min}}} \leq \omega_{\mathrm{m}} \leq \omega_{\mathrm{m_{max}}} \\ \mathrm{SOC_{min}} \leq \mathrm{SOC} \leq \mathrm{SOC_{max}}, \end{cases} \tag{1}$$

where T_e denotes the torque of the ICE, ω_e denotes the speed of the ICE, T_m denotes the torque of the EM, and ω_m denotes the speed of the EM.

In the research regarding EMSs, the energy management issues can be transformed into a cost function problem with different optimization goals (Gu et al., 2019). Generally, the energy management issues can be transformed into the energy management issue of the SOC, the energy management issue of equivalent fuel consumption, the energy management issue of the instantaneous condition, and the energy management issue of emissions.

2.1 The energy management issue of the SOC

The battery is the key component of HEVs, and the SOC is closely related to the battery capacity and charge–discharge characteristics. If the SOC is too high or too low, it will affect the performance of the battery. Thus, it is necessary to control the working range of the SOC, and many EMSs take the SOC as one of the optimization goals, aiming to optimize the working range and prolong the service life of the battery. Therefore, the SOC can be regarded as a threshold value that limits the operation interval of the EMS; it can also be regarded as a weighting item for calculating the cost function of the HEV. In addition, frequent charging and discharging will affect the life of the battery, thereby affecting its output power. X. Hu et al. (2020) state that the loss and degradation of the battery can affect the accuracy of the EMS; thus; the state of health is introduced into the EMS. The expression in the cost function is as follows:

$$\begin{cases} C_{\mathrm{bat},j} = M_{\mathrm{bat}}(\mathrm{soh}(t_\mathrm{k}) - \mathrm{soh}(t_\mathrm{k} + t_\mathrm{p})) \\ N = \frac{3600 A_{\mathrm{tol}}}{Q} \\ \mathrm{soh}(t_\mathrm{k}+1) = \mathrm{soh}(t_\mathrm{k}) - \frac{|i(t_\mathrm{k})|\Delta t}{2NQ}, \end{cases} \tag{2}$$

where $C_{\mathrm{bat},j}$ denotes the cost item of the battery degradation in the cost function, which constitutes the cost function of the EMS and other items; $\mathrm{soh}(t_k)$ denotes the state of health of the battery; M_{bat} denotes the cost of the battery system; Q denotes the nominal capacity of the battery; N denotes the number of cycles at the end of battery life; A_{tol} denotes the total discharged Ah (ampere hour) throughput; and $i(t_k)$ denotes the current of the battery.

2.2 The energy management issue of equivalent fuel consumption

While calculating the cost of a HEV, the energy consumption is usually converted into the sum of the fuel consumption of the ICE and the power consumption of the EM, which can be regarded as the equivalent fuel consumption. Generally, the cost function is applied to describe the equivalent fuel consumption. The proportion of the fuel consumption of the ICE and the power consumption of the EM in the cost function can be adjusted according to the actual driving conditions to make the control more accurate. This energy management issue can be described as follows (Wang et al., 2017a):

$$\begin{cases} J = \int_{t_k}^{t_{k+p}} [\alpha_1(t) f(t) + \alpha_2(t) g(t)] \mathrm{d}t \\ \mathrm{EF}(t) = \frac{\alpha_2(t)}{\alpha_1(t)}, \end{cases} \tag{3}$$

where J denotes the energy consumption cost function of the HEV in the period from t_k to t_{k+p}, including the fuel consumption cost $f(t)$ and the power consumption cost $g(t)$; $\alpha_1(t)$ denotes the weighting coefficient of the fuel consumption; and $\alpha_2(t)$ denotes the weighting coefficient of the power consumption. The equivalent factor (EF) can be defined as $\mathrm{EF}(t)$ and can convert the power consumption cost into the fuel consumption cost. The EF can be regarded as a fixed value designed based on experience, or it can be designed as an adaptive EF that is adjusted in real time according to the characteristics of the EM and the battery. The optimization goal of this energy management issue is to minimize the cost function over a period or instantaneously.

2.3 The energy management issue of instantaneous conditions

During the HEV driving process, the vehicle may experience instantaneous driving conditions, such as start–stop and gear shifting, over a long period. Frequent starting and stopping of the ICE will cause an increase in fuel consumption. Therefore, the fuel consumption of instantaneous conditions is usually converted into the cost function. According to the model of instantaneous conditions, the fuel consumption of shifting, frequent starting and stopping of the ICE, and starting and braking conditions are considered. They can be regarded as the weighted terms in the cost function, which improve the accuracy of the cost function and can better reflect the fuel consumption during actual driving. In Yan et al. (2012), the fuel consumption during the ICE start–stop process is added into the EMS, which forms the cost function along with the SOC and equivalent fuel consumption.

$$\begin{cases} J = \int_{t_k}^{t_k+t_p} \{\alpha_1(t) f(t) + \alpha_2(t) g(t) \\ \qquad + \alpha_3(t)[1 - \mathrm{key\_on}(t_k + t_p)]\} \mathrm{d}t \\ g(t) = \mathrm{SOC}(t_k) - \mathrm{SOC}(t_k + t_p) \end{cases} \tag{4}$$

Here, the first term denotes the equivalent fuel consumption of the HEV within time interval t_p, the second term denotes the equivalent fuel consumption of the SOC within the time interval, the third term denotes the equivalent fuel consumption of the ICE start–stop process, $g(t)$ can be defined as the function of the SOC, $\mathrm{key\_on}(t)$ denotes the start or stop state of the ICE, and $\alpha_3(t)$ denotes the weighting coefficients of the fuel consumption cost caused by the start–stop state of ICE in the cost function.

In Y. Qi et al. (2017), experimental data from the ICE are applied to solve the dynamic response model of the ICE and the controller, and they are introduced into the cost function along with the output characteristics of the EM in order to reduce the impact of ICE instantaneous characteristics on energy management issues.

$$J = \int_{t_k}^{t_k+t_p} \begin{bmatrix} \omega_{\omega e}(t)\left(\omega_e(t) - \omega_e^{\mathrm{ref}}(t_k)\right)^2 + \omega_{te}(t) \\ \times \left(T_e^{\mathrm{act}}(t) - T_e^{\mathrm{ref}}(t_k)\right)^2 \\ + \omega_{\omega A}(t)\left(\omega_m(t) - \omega_m^{\mathrm{ref}}(t_k)\right)^2 \\ + \omega_{De}(t)(D_e(t))^2 \end{bmatrix} \mathrm{d}t \tag{5}$$

As the perdition control model, t_k denotes the time at the kth prediction horizon, and t_p is the time duration of the prediction horizon; $\omega_{\omega e}(t)$, $\omega_{te}(t)$, $\omega_{\omega A}(t)$, and $\omega_{De}(t)$ denote the respective weight function of the reference ICE target speed, reference target torque of the ICE , reference target speed of EM, and reference fuel consumption rate of the ICE (which can also be regarded as the penalty functions); $\omega_e^{\mathrm{ref}}(t_k)$, $T_e^{\mathrm{ref}}(t_k)$, and $\omega_m^{\mathrm{ref}}(t_k)$ denote the reference values of the respective ICE speed, output torque of the ICE, and EM speed; $D_e(t)$ denotes the reference index of the fuel consumption rate of the ICE.

2.4 The energy management issue of emissions

The emergence of HEVs has stemmed from the requirement to save energy and reduce emissions. The EMS is not only related to the dynamic performance but also directly affects the emission performance of vehicles. Therefore, emission indicators and emission control are integrated into the study of energy management issues. The emission of pollutants such as CO_2 and NO_x is usually introduced into the cost function through certain methods, and the cost function is constructed to explore the multi-objective optimization of energy consumption and emissions. (Nüesch et al., 2014a).

$$J = \int_{t_k}^{t_k+t_p} [\alpha_1(t) f(t) + \alpha_2(t) g(t) + \mu \mathrm{ER}_n(t)] \mathrm{d}t, \tag{6}$$

where ER_n denotes the calculated value of specific emissions (NO_x), and μ is the weighting coefficient of the emission performance. A larger value of μ indicates that the cost function pays more attention to emission performance, whereas a lower value of μ indicates that energy consumption is more important in the search for the instantaneous optimal solution.

3 The rule-based energy management strategy

The rule-based EMS is one of the most important EMSs applied to HEVs. The principle of this EMS is relatively simple, and it does not require the use of a complex algorithm; therefore, it has been widely used in early-stage engineering (Jalil et al., 1997). At present, there are two main forms of rule-based EMS: one is the deterministic rule-based EMS, which regulates the working state of various vehicle parts according to different driving demands and the working range limits; the other is the fuzzy logic rule-based EMS, In the latter EMS, according to multi-input and time-varying characteristics, the advantages of fuzzy logic control are integrated into the EMS, the membership function (MF) of state variables and the rate of change of state variables are established, and the fuzzy logic rules are determined for energy management and the SOC regulation. The rule-based EMS is based on experience, the driving mode, and a static map, and it is widely used and less affected by the external interference. The idea is simple and easy to implement, and it can be designed based on the existing vehicle control concept. In addition, modern algorithms such as NNs and GA can be used to optimize the EMS, which can improve its adaptability, to a certain extent, with respect to dealing with complex dynamic changes. However, the engineering experience directly determines the performance of the EMS, and it is difficult to obtain the optimal control effect.

3.1 The deterministic rule-based energy management strategy

In this EMS, the deterministic rule was established based on the parameter characteristics of each component, existing engineering experience, and research results. It can adjust the working status and power distribution according to the driving demands and the working conditions of each component. The main idea of this EMS is to use the EM to adjust the working range of the ICE so that the ICE is always working in the high-efficiency range. In addition, it is necessary to combine the battery to select a suitable driving mode for the HEV. The input variables of this EMS are mostly the demand power and the SOC. It has an optimization effect for any driving condition, with certain adaptability. Generally, the deterministic rule-based EMS can be divided into the logic threshold strategy and the "following" strategy. The logic threshold strategy takes the limiting conditions, such as the ICE working point and the SOC as threshold, and adjusts the working state of each component according to the threshold. The following strategy tracks one or more operating parameters and uses them as a basis to adjust the operating status of each component. The tracking parameter is mostly the output power of the ICE. Although, there are also EMSs that set the speed or the load as the tracking parameter.

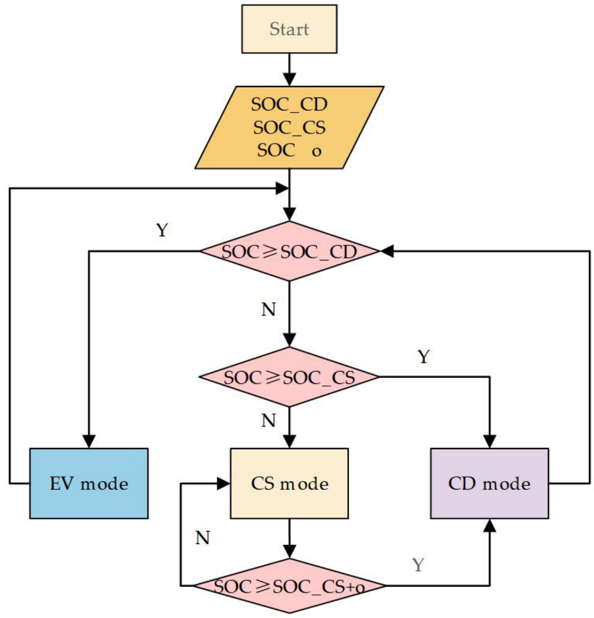

Figure 2. Mode-switching control of the logic threshold strategy.

3.1.1 The logic threshold strategy

The working modes can be divided into the EV mode, the charge-depleting (CD) mode, and the charge-sustaining (CS) mode, according to the SOC threshold: in EV mode, the EM is driven separately; in CD mode, the working state of the ICE and EM is adjusted according to the high-efficiency interval of the ICE; and in CS mode, it is necessary to maintain the SOC around a threshold. In addition, one can switch between the CD and CS modes; thus, the working point of the ICE is always in the efficient range, and the working state of the EM is judged according to the driving demands (Peng et al., 2015). The mode-switching control of the logic threshold strategy is shown in Fig. 2.

In Y. Liu et al. (2019), a logic threshold strategy based on the efficiency range of the ICE and the optimal operating range of the battery was proposed to keep the SOC at a high level and improve the efficiency of the ICE. In Asghar et al. (2018), an EMS based on the Atkinson cycle ICE was established, and the driving mode was determined according to the speed and torque demand. Based on the fuel cell hybrid power system, the SOC of fuel cells and lithium batteries and the voltage state of supercapacitors were set in Y. Wang et al. (2019), and the logic threshold strategy was proposed to assign the different working states of various components. The system can utilize the charge–discharge limitations of power capacity and residual energy to extend the service life. In Hao et al. (2016), the working range of the ICE and battery, the minimum throttle opening of the ISG (integrated starter generator) motor and EM auxiliary conditions, and the minimum vehicle speed of the EM driving conditions were used as the threshold. The direct algorithm can transform the EMS into a direct optimization problem of seven-dimensional parameters. In Jeoung et al. (2019), the start–stop of the ICE was controlled according to the threshold of demand power, torque, and speed, and the battery charge–discharge process was determined according to the SOC threshold in which the charge–discharge speed can be used as a threshold. In Xia and Zhang (2015), an EMS based on the quadratic performance index which was independent of future driving conditions was proposed. The operating conditions of the ICE and EM were adjusted according to the speed and SOC as well as the expected speed and SOC values. In Padmarajan et al. (2016), an EMS based on mixed rules was proposed. The driving information and estimated vehicle trip energy were combined with a blended charge-depletion strategy to reduce the ICE start–stop times. In Zhou et al. (2018), the working state of the ICE was determined according to the SOC threshold, and DP was applied to determine the optimal trajectory of the ICE and the corresponding SOC threshold.

3.1.2 The following strategy

The following strategy can be divided into the power-following strategy (PFS), the speed-following strategy (SFS), and the load-following strategy (LFS). The essence of the PFS is to ensure that the output power of the ICE and EM as well as the vehicle load power match the sum and maintain ICE function within the highly efficient range (Li, 2019). The SFS adjusts the driving conditions in real time according to the speed. The LFS mainly adjusts the charge–discharge process of the battery according to the power demand and indirectly adjusts the working state of each component. At present, the most widely used strategy is the PFS.

In Li (2019), discrete speed switching and the best fuel consumption curve of the PFS were compared. The performance of the best fuel consumption curve of the PFS was better. In Zuo et al. (2009), a full-vehicle mode transition algorithm was proposed to switch vehicle modes, and a PFS based on the minimum fuel consumption curve of the ICE was adopted using the planetary row kinematics limit model. In Luo et al. (2019), the PFS was combined with two HEV DC-line voltage control strategies (CVPI, complete zero voltage switching control, and PZVS, persistent zero voltage switching control). According to the minimum mass point of the equivalent fuel consumption, the comparative study showed that the PFS PZVS had better fuel economy. In B. Zhang et al. (2020), an adaptive smoothing PFS based on the optimal efficiency graph was proposed, dividing the demand power into the trend and the fluctuation parts. The trend part was provided by the ICE, and the fluctuation part was provided by the supercapacitor. In Chen et al. (2019), according to the closed solution of optimal power diversion, the truncated battery-following strategy was developed to reproduce the global optimization solution of DP. In Geng et al. (2019), an on/off PFS optimized by fuzzy logic was proposed for a fuel cell HEV and was used for extended controllers. In Mohamed et al. (2019), two following strategies were proposed to select the driving mode of the HEV: one was the SFS, which selected the start–stop of the ICE according to the vehicle speed, and the other was the LFS, which selected the operating mode according to a set power threshold and the SOC. This comparative research found that the energy-saving effect of the LFS was better. In Bizon (2019), an EMS based on the LFS and real-time optimization was proposed to evaluate the fuel cell economy and efficiency performance indicators. Weighting coefficients were applied to mix performance indicators into an optimization function.

The characteristics of different deterministic rule-based EMSs are illustrated in Table 2. The deterministic rule-based EMS has a simple control process, convenient parameter adjustment, good robustness, and good stability. However, this EMS does not provide the best performance; instead, it provides a range of preliminary optimization in a specific driving cycle or instantaneously. In addition, the control rules of the deterministic rule-based EMS are mainly based on engineering experience and test data, which have many uncertainties and cannot meet the time-varying requirements of HEVs. Moreover, there are obvious limitations in the actual control process, and this method cannot entirely utilize the energy-saving advantages of HEVs. Therefore, in the study of deterministic rule-based EMS, optimizing multiple control parameters is of great significance to improve vehicle performance.

3.2 The fuzzy logic rule-based energy management strategy

Fuzzy control is a kind of control method with strong robustness, easy adjustment, and strong adaptability that can imitate the uncertain thinking mode and logic of the human brain. Fuzzy control uses the MF to reason some systems with strong uncertainty, nonlinearity, or an unknown mathematical model; to solve problems that are difficult to solve using conventional methods; and to simplify the calculation process. The main process of fuzzy control is “fuzzification” and “defuzzification”, and the core component is the fuzzy logic controller. The input signals are transmitted to the fuzzy logic controller where they are fuzzified, and the fuzzy results are then obtained according to the MF. Following this process, the fuzzy results are defuzzified to obtain the output signals used for precise control (Jager, 1995). Generally, the input signals of HEVs are the power demands obtained from the pedal signal and ground information, combined with the status parameters, the working state, and the output power

Table 2. Summary of exemplary works on deterministic rule-based EMSs

Reference	Approaches	Application scenarios	Verification	Performance
Zuo et al. (2009)	Power-following strategy with parameter limits	Series-parallel HEV	Simulation	– Used the UDC – Fuel consumption was 55.24 % lower than the ICE driving condition
Peng et al. (2015)	SOC threshold strategy	Plug-in hybrid electric bus	Simulation	– The SOC is stabilized at around 30 % – 13.7 L per 100 km diesel consumption – 10.5 kW h per 100 km electricity consumption
Xia and Zhang (2015)	Speed and SOC threshold strategy	Power-coupling HEV	Simulation	– Based on the quadratic performance index – Negligible calculation required – Fuel economy was very close to the PMP
Y. Liu et al. (2019)	ICE efficiency threshold strategy	Power-split HEV	Simulation	– The SOC was stabilized at around 60 % – The ICE always works in an efficient range
Li (2019)	PFS considering the SOC	Six-wheel skid-steering series HEV	Simulation	– Compared with the multispeed switching PFS, fuel consumption was reduced by 9.35 % – After considering the SOC, fuel consumption was further reduced
Mohamed et al. (2019)	SFS and LFS	Parallel HEV	Simulation	– Used the normalized European driving cycle – The energy-saving effect of the LFS was better than the SFS
Bizon (2019)	LFS	Fuel cell hybrid power system	Simulation	– Weighting coefficients were applied to mix performance indicators into an optimization function to improve fuel economy.
B. Zhang et al. (2020)	Adaptive smoothing PFS	Series-tracked hybrid bulldozer	HIL	– Compared with the PFS based on experimental data and the ICE minimum fuel consumption curve, the equivalent fuel-saving ratio was improved by 7.8 % and 3.4 %, respectively

HIL denotes hardware in loop. UDC refers to the Urban Driving Cycle.

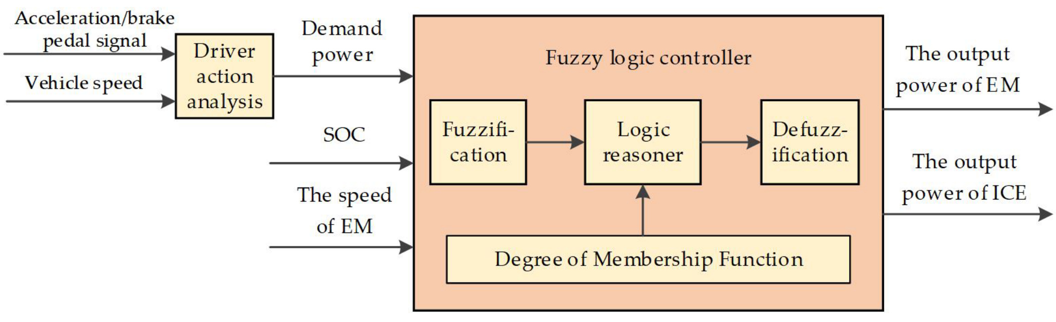

Figure 3. The basic principles of a fuzzy logic rule-based EMS.

of each component, which are obtained through fuzzification and defuzzification (Li, 2008). The basic principle of a fuzzy logic rule-based EMS is shown in Fig. 3.

The following outlines the application of traditional fuzzy logic rule-based EMSs to HEVs. In Hemi et al. (2014), an EMS based on fuzzy logic was proposed that took the demand power and SOC as the input for the fuzzy logic controller and considered the influence of regenerative braking on the battery in the MF design process in order to meet the power demand and protect the battery. In Ma et al. (2019), an EMS based on fuzzy logic that took the SOC and demand torque as inputs was proposed to optimize the torque output. The MF was established according to the SOC, and the output torque of the ICE and the auxiliary output of the EM were obtained. According to the real-time transmission efficiency of HEVs, a fuzzy logic rule-based EMS was proposed based on the optimal working line of the ICE and mechanical point control strategy in S. Wang et al. (2019a) to realize the synchronous improvement of transmission efficiency and fuel economy. In Mahyiddin et al. (2016), a triangular MF was established for the battery charge–discharge process and power split. Fuzzy logic was used to distribute the output power between various power sources to compensate for the power flow performance. In Denis et al. (2015), an EMS based on fuzzy logic was established according to past and current driving information as well as the expected travel distance, and DP was adopted to optimize it. In addition, the driving information was used to achieve adaptive control of different driving conditions. In Singh et al. (2020), the regenerative braking process was introduced into the fuzzy logic controller, requiring the ICE and EM to work in an efficient interval. The MF was designed based on the driving demands and fuel economy.

With deepening research into HEVs, the adaptability of EMSs has become more and more critical, and the adaptive fuzzy logic rule-based EMS has been proposed and gradually applied. In X. Zhang et al. (2017), a fuzzy EMS based on the optimization algorithm of the adaptive neural fuzzy system was proposed that took the demand torque of the clutch and SOC as input and the torque of the ICE as output. Gradient search technology was applied to adjust the weight of each layer and the output results so that the least squares method between the actual output and the expected output could reach the minimum. In Tian et al. (2018), an adaptive fuzzy logic rule-based EMS for hybrid city buses was established according to the optimal SOC curve. An NN was used to learn the best SOC curve and realize the planning and control of the battery working state according to future driving information from the online ITS and navigation system. In Shen et al. (2020), the efficiency and power change rate of the fuel cell were considered to balance the load of the power system, and the power slope of the fuel cell was limited to prevent the abrupt change. An incremental fuzzy logic EMS was proposed to ensure that the fuel cell was working in the high-efficiency range and to prolong its life. In Sabri et al. (2018), a dedicated fuzzy logic EMS for "through-the-road" HEVs was proposed that determined the power flow based on the global discharge rate obtained from the current vehicle speed, SOC, and remaining travel distance and also gave priority to the output from the electric drive system. In Sölek et al. (2019), an EMS combined with online and off-line algorithms was proposed. The online algorithm used fuzzy logic to select the control method and the driving mode, and the off-line part was established based on the average consumption data in EV mode.

With the advancement of computer science, various real-time algorithms have been proposed, and the fuzzy logic EMS based on algorithm optimization has gradually been applied. In Shi et al. (2018), the energy management issue was described as a predictive control problem. A Markov chain was used to solve the power demands and speed in the predictive layer. A fuzzy logic controller was used to achieve optimal tracking of the ICE speed in order to ensure that the ICE could realize the desired power stably. In Peng and Xie (2017), the MF of the EMS based on fuzzy logic was optimized using the GA to solve the SOC maintenance and power distribution problems. In addition, the CO and NO_x emissions were taken into consideration. In Meng et al. (2017), a fuzzy logic EMS based on GA optimization was proposed. The GA was used to optimize the MF based on historical data, which effectively prevented the EM from generating peak torque, and the ICE mostly worked in the efficient zone. In Singh et al. (2021), an EMS based on fuzzy logic and Ehrman NNs was proposed. The optimized fuzzy logic controller's input was the demand torque, the SOC, and regenerative braking, which aimed to maximize fuel economy while maintaining battery health. In Liu et al. (2017), an EMS based on fuzzy logic and RL was proposed. Fuzzy logic and Q-learning were used to realize speed prediction, and RL was used to learn the transition probability of power demand. In Q. Xu et al. (2018a), a dual-optimization fuzzy logic EMS based on the GA and DP was proposed: the GA was used to optimize the MF, and DP was used to optimize the fuzzy logic controller. The braking energy recovery was considered. In Mohammad et al. (2020), a fuzzy logic EMS based on the social spider algorithm was proposed to adjust the scaling factor in the MF in real time to reduce speed-tracking errors.

The characteristics of different fuzzy logic rule-based EMSs are illustrated in Table 3. In the control process, the fuzzy control is not completely dependent on the precise mathematical model, which can greatly reduce the amount of calculation required. It also has high efficiency, good robustness, and good economy. However, when designing fuzzy rules and the MF, there are no certain rules to be followed. Instead, it is an experience-based EMS that cannot take full advantage of the energy-saving and emission reduction potential of HEVs; therefore, it is not the optimal solution in the scientific sense. In addition, the fixed control law leads to poor dynamic characteristics of the system, which makes it difficult to realize real-time control and optimization. Therefore, in the current research process, the GA, NNs, and RL are often used to optimize fuzzy logic in order to improve the real-time application and controllability of fuzzy control.

4 The optimization-based energy management strategy

In the optimization-based EMS, the cost function is designed to combine the structural parameters of each vehicle component and constraint. This EMS minimizes the cost function to optimize the control objective. The control objective is fuel consumption. Some scholars also integrate parameters

Table 3. Summary of exemplary works on fuzzy logic rule-based EMSs.

Reference	Approaches	Application scenarios	Verification	Performance
Denis et al. (2015)	Fuzzy logic Blended control DP optimization	Plug-in HEV	Simulation	– The driving information and the expected travel distance were taken into consideration – Fuel consumption was reduced by 27 %
Liu et al. (2017)	Fuzzy logic RL	Parallel HEV	HIL	– Q-learning-based speed prediction – RL-based power demand TPM learning – Fuel consumption was 17.54 % lower than rule-based EMS
Sabri et al. (2018)	Fuzzy logic Global discharge rate	Through-the-road (TtR) HEV	Simulation	– Fuel economy improved by 19.8 % (HWFET) – Fuel consumption was 7.48 L per 100 km (NEDC) and 3.28 L per 100 km (HWFET)
Ma et al. (2019)	Fuzzy logic	Parallel HEV	Simulation	– The fluctuation in the SOC variation was lower – Fuel consumption was reduced by 13.3 % and 4.5 %
S. Wang et al. (2019a)	Fuzzy logic Mechanical point	Power-split HEV	Simulation	– Improved the transmission efficiency and fuel economy synchronously
Singh et al. (2020)	Fuzzy logic	Series-parallel HEV	Simulation HIL	– Considered regenerative braking – Fuel consumption was 4.9 L per 100 km. – Fuel economy improved by 50.56 %
Mohammad et al. (2020)	Adaptive fuzzy logic Social spider algorithm	Fuel cell HEV	Simulation	– The MF of social spider algorithm optimization – Fuel economy and reference speed-tracking were better than power-tracking control
Singh et al. (2021)	Fuzzy logic Ehrman NNs	Power-split HEV	Simulation HIL	– Kept the battery healthy – Fuel consumption was 13.49 $\mathrm{km\,L^{-1}}$ (NEDC), 20.5 $\mathrm{km\,L^{-1}}$ (UDDS), and 61.13 $\mathrm{km\,L^{-1}}$ (FTP)

TPM represents transfer probability matrix. HWFET refers to the Highway Fuel Economy Test cycle. NEDC refers to the New European Driving Cycle. UDDS refers to the Urban Dynamometer Driving Schedule. FTP represents Federal Test Procedure.

such as the battery power consumption, emissions, and the battery health level into the cost function for multi-objective optimization. In general, the optimization-based EMS can be divided into two categories: one is the global optimization EMS, which takes the operating cost of the whole driving condition as the optimization objective and utilizes the optimal control theory based on historical data to conduct global optimization, and the other is the instantaneous optimization EMS, which takes the instantaneous fuel consumption and other parameters as the optimization objectives. Combined with the instantaneous parameters, it controls the working state of each power source and instantaneously minimizes the cost function under unknown driving conditions.

4.1 The global optimization energy management strategy

In the research regarding the global optimization EMS, representative methods include the DP-based EMS and the PMP-based EMS. In addition, intelligent algorithms such as the GA, GT, and CO are also applied to the global optimization EMS. A comparison of these different methods is shown in Table 4, which illustrates the pros and cons of each method. The global optimization EMS is usually optimized for a fixed cycle of driving conditions, which has a certain theoretical guiding significance and is suitable for HEVs with relatively fixed working conditions. However, under unknown driving conditions, the global optimization solution is not the optimal result in practical sense. Therefore, it is suitable to be used as a reference for the control effect of other EMSs.

4.1.1 The DP-based energy management strategy

DP is a mathematical method to solve the optimization of the multistage decision process and was applied to the HEV energy management issue around 2000. The entire interval of the energy management issue is discretized into multiple intersections by DP. Appropriate control variables are then selected according to each intersection. The solution of the

Table 4. The comparison of different methods applied to the global optimization EMS.

Approaches	Pros	Cons
DP	– Global optimization results – The reference of other EMSs	– Prior knowledge of driving cycle – Poor adaptability – Low calculation efficiency
PMP	– Near-optimal control – High calculation efficiency	– Relies on accurate predictive models – Less adaptability – Needs the Hamiltonian function and co-state estimation
GA	– Strong adaptability and self-learning – Comprehensive search of the global optimization solution	– Accuracy cannot be quantified – Prone to premature convergence – High calculation complexity
GT	– Strong robustness – Multi-input optimization – Independent of driving cycle	– Less adaptability – High calculation complexity – Assumption of complete rationality
CO	– Consistent value of the local optimal and global optimization – High calculation efficiency	– Small range of application – Relies on a convex model

first intersection is used as a reference for the solution of the next intersection, and the solutions that could reach the optimal value are retained until the last intersection. DP is often used to optimize conventional fixed driving routes, such as hybrid electric buses. In DP-based EMSs, the input parameters are the driving cycle information and the constraints. The energy management issue is discretized and can be converted into the problem that calculates all paths from beginning to end. The global optimization result is the sum of the results of each step. The principle of a DP-based EMS is shown in Fig. 4.

However, it is impossible to predict the whole driving process under actual driving conditions, and the calculation is heavy and time-consuming, so it cannot be applied to real-time control (Bertsekas, 1995). Therefore, the adaptive DP and the heuristic DP have been proposed. Combined with historical information, they can improve the real-time performance of the traditional DP method. In recent years, the stochastic DP (SDP) was proposed based on DP, which discretized the driving conditions through power demand and speed, and established probability transfer matrices of the current and next moment based on a Markov chain in order to estimate the power demand and other parameters at the next moment (Birge and Louveaux, 1997). This method is based on historical driving data and does not require a complete driving cycle. It can obtain the optimal control rate and realize real-time control to a certain extent. However, there is still a certain deviation between the predicted demand and the actual demand by the Markov chain. The adaptability of SDP to multiple working conditions still needs to be improved.

Due to its excellent performance with respect to solving the multistage decision optimization problem, DP has been introduced to EMSs. In H. Li et al. (2019), a DP-based EMS was proposed that considered the SOC as the state variable, the transmission ratio of continuously variable transmission (CVT), and the electric torque distribution between power sources as the output to solve the minimum value of total fuel consumption. Due to the large computation burden and long computation time of the DP-based EMS, a respective local linear approximation and a quadratic spline approximation were used in Larsson et al. (2015) to shorten the calculation time and reduce the storage pressure. In Delkhosh et al. (2020), DP was adopted to find the best operating mode at each point in the HEV operating region. The EMS is established according to the optimal operating region to realize the conversion of the operating modes. In Pam et al. (2019), the influence of ramp resistance on fuel economy was accurately quantified using DP. An EMS considering ramp resistance was proposed to reduce the fuel consumption calculation error caused by ignoring the ramp. With the aim of applying a DP-based EMS to plug-in HEVs, Wang et al. (2015) overcame the numerical problems between the optimization accuracy and calculation burden and further exploited the energy-saving potential of DP-based EMSs.

However, DP-based EMSs have some limitations under unknown driving conditions. Therefore, scholars have proposed adaptive DP and heuristic DP based on traditional DP. In Kalia and Fabien (2020), an EMS based on distance-constrained adaptive real-time DP for extended-range electric vehicles was proposed. This strategy monitored the SOC

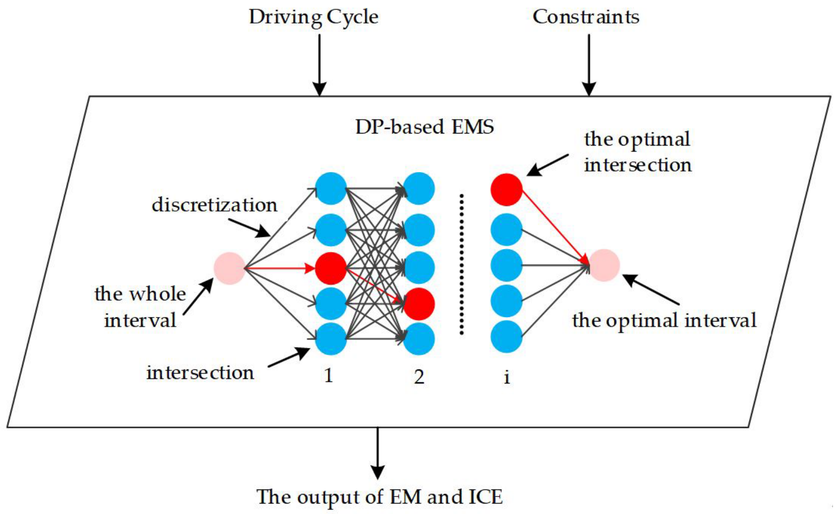

Figure 4. The principle of a DP-based EMS.

deviation from the calculated optimal state. It recalculated the optimal parameters accordingly to approach the real-time control and improve the adaptability and fault tolerance. In Zheng and Mi (2009), an adaptive DP-based EMS that combined DP with fuzzy logic was proposed. Firstly, the optimization results were obtained by DP, and the efficiency of each power point of the ICE was analyzed to reduce the degrees of freedom of the EMS. The MF was then established according to the ratio of the ICE power to system power, speed, acceleration, and SOC. In Liu et al. (2019), a heuristic DP-based EMS was proposed for the online optimization of HEVs. A back-propagation NN (BPNN) was adopted to build a vehicle model that reflected the actual dynamic process of HEVs. According to the dynamic model, an online algorithm was used to optimize the energy management process of heuristic DP. In Li and Görges (2019a), a heuristic DP-based EMS was proposed that was combined with the adaptive cruise control in order to ensure the distance from the vehicle in front. Moreover, an action-dependent heuristic DP was used to realize active distance control. This EMS can adjust internal vehicle parameters online to deal with system disturbances and achieve the economy and drivability requirements. In Li and Görges (2019b), the NN-based shift control was combined with the action-dependent heuristic DP-based power distribution control, and a real-time adaptive EMS was proposed that supported the online learning of the controller and could significantly reduce the calculation load of DP and improve the calculation speed.

In addition, SDP has also been applied to EMS to improve real-time performance and adaptability. In Opila et al. (2012, 2013), an EMS based on the shortest-path SDP was proposed in which the driving cycle was modeled as a finite-state Markov chain. The cost function consisted of a weighted sum of fuel consumption and drivability losses from shift and ICE-switching events. By changing the weight of each component, both drivability and fuel economy could be improved. In Qin et al. (2017), an SDP-based EMS for a pre-transmission single-shaft torque-coupling parallel HEV was proposed. The driver's demand torque was modeled as a Markov process to represent the uncertainty of future driving conditions. In Elbert et al. (2015), an SDP-based EMS was proposed in which the state update function consisted of a random model of driver behavior represented by a Markov chain and a deterministic vehicle model. This strategy considered multiple objectives such as fuel economy and drivability while reducing the calculation burden. In Du et al. (2016), an EMS based on SDP and the ECMS was proposed. In the off-line part, SDP was used to divide the historical fixed path driving information into multiple sections. The driving condition model of each section was then established using a Markov chain to solve the minimum fuel consumption.

The characteristics of different DP-based EMSs are illustrated in Table 5. Although the DP method can solve the global optimization solution, it is based on a known travel period. For unknown working conditions, DP obviously cannot meet the actual driving demands of vehicles. The efficiency of energy management is uncertain, so it cannot be directly applied to EMSs and often needs to be combined with other methods.

In addition, the calculation burden of the DP method increases sharply with increases in the system dimension. Using the proposed adaptive DP, heuristic DP, and SDP methods, the traditional DP method combined with various optimization methods can expand the application scope and achieve near-real-time optimization. In addition, according to the characteristics of DP, a variety of acceleration algorithms are also applied to improve the calculation efficiency. At present, the DP-based EMS is mainly used in HEVs with fixed driving conditions, including hybrid electric buses and

Table 5. Summary of exemplary works on DP-based EMSs.

Reference	Approaches	Application scenarios	Verification	Performance
Du et al. (2016)	Stochastic DP ECMS	Plug-in hybrid electric bus	Simulation HIL	– Divided historical driving information into multiple sections – A stochastic driving condition model based on a Markov chain – Fuel economy was improved by 7.8 %
Qin et al. (2017)	Stochastic DP	Parallel HEV	Simulation	– Demand torque was modeled as a one-state Markov process to represent the uncertainty – Improved the efficiency of the driving system
H. Li et al. (2019)	DP	HEV equipped with CVT	Simulation	– Considered the CVT speed ratio – Fuel consumption was 10 % (NEDC), 13.1 % (HWFET), 8.6 % (UDDS), and 13.7 % (WLTC) lower than the ECMS
Pam et al. (2019)	DP Slope resistance	Parallel HEV	Simulation	– Considered the influence of ramp to improve the accuracy of the EMS – The error was 0.4 % with the road slope but 9 % without the road slope
Liu et al. (2019)	Heuristic DP BPNN	Plug-in HEV	Simulation Experiment	– A practical route in the Beijing road network – Online vehicle model was built using BPNN to accurately reflect the real dynamic process – Fuel consumption was 4 % lower than off-line
Li and Görges (2019b)	Action-dependent heuristic DP NN	Parallel HEV	Simulation	– NN-based gearshift control – Independent of the system model – Allowed learning and improved efficiency – Fuel economy was near DP optimal results
Delkhosh et al. (2020)	DP Electric assist control strategy	Parallel HEV with CVT	Simulation	– Found optimal operating regions – Reduced the sensitivity of the electric assistant control strategy to the driving behavior
Kalia and Fabien (2020)	Adaptive real-time DP	Extended-range electric vehicles	Simulation	– Considered the distance constraints – Monitored the SOC deviation online and adjusted the optimal control parameters

WLTC refers to the Worldwide harmonized Light vehicles Test Cycles.

hybrid electric mine cars. It is often used as a reference to verify the performance of other EMSs.

4.1.2 The PMP-based energy management strategy

Pontryagin's minimum principle is also called Pontryagin's maximum principle. When the state or input is restricted, the optimal control signal from one state to the next state is obtained. The PMP-based EMS mainly achieves global optimization control of HEVs by solving the minimum value of the Hamiltonian. The Hamiltonian function is obtained by combining parameters such as the SOC, fuel consumption, and demanded power with a mathematical model of the HEV, and the optima global solution can be obtained according to the driving conditions (Wu, 2018). A flow chart of the PMP-based EMS is shown in Fig. 5.

In PMP-based EMS, the cost function can be defined as follows:

$$J(u) = K(t_\mathrm{b}) + \int_{t_\mathrm{a}}^{t_\mathrm{b}} L(x(t), u(t), t)\mathrm{d}t, \tag{7}$$

where t_a and t_b denote the respective initial moment and the end moment, u denotes the control variable, $K(t_\mathrm{b})$ denotes the terminal constraint, $L(\ )$ denotes the objective function, and $x(\ )$ denotes the boundary condition.

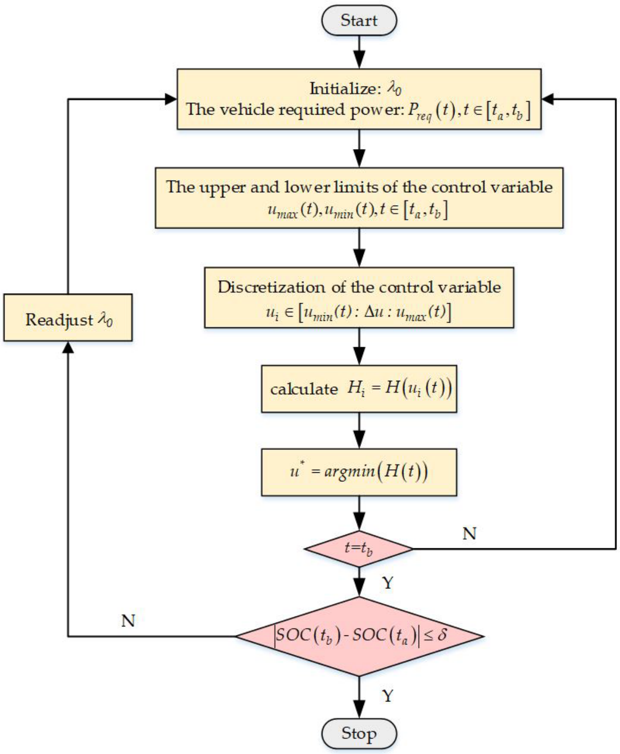

Figure 5. The flow chart of the PMP-based EMS.

The Hamiltonian function H can be defined as follows:

$$H(x(t), u(t), \lambda(t), t) = \lambda_0 L(x(t), u(t), t) + \lambda^T h(x(t)u(t)t), \quad (8)$$

where $\lambda(t)$ denotes the co-state variable, and $h(\,)$ denotes the state function.

When t_b is fixed, for the state quantity of the domain, the state at the initial time and the end time are determined, and the state equation and co-state variables satisfy the following conditions:

$$\begin{cases} \dot{x}^*(t) = \nabla_\lambda H_{|*} = h(x^*(t), u^*(t), t) \\ x^*(t_a) = t_a x^*(t_b) = t_b \\ \dot{\lambda}^*(t) = -\nabla_x H_{|*} = -\lambda_0^* \nabla_x L(x^*(t), u^*(t), t) \\ \qquad -\left[\frac{\delta h}{\delta x}(x^*(t), u^*(t), t)\right]^T \lambda^*(t). \end{cases} \quad (9)$$

For all of the control variables in the domain, the value of H at the optimal control variable is the smallest.

$$H(x^*(t)u^*(t)\lambda^*(t)\lambda_0^* t) \le H(x^*(t)u(t)\lambda^*(t)\lambda_0^* t) \quad (10)$$

Compared with DP, the PMP-based EMS achieves global optimization with less calculation, which is equivalent to the optimization effect of DP, and is more suitable for real-time control. However, without establishing an accurate real-time predictive model, instantaneous optimization still cannot be achieved.

In Sanchez and Delpra (2018), a PMP-based EMS was proposed to optimize calculation. A Q-trick method was proposed to transform the energy management issue into a boundary value problem and accelerate the operation process. Based on the assumption that the battery's internal resistance and open-circuit voltage are independent of the SOC, instantaneous optimal control with appropriate battery usage equivalent parameters can result in the global optimization solution. According to these findings, a PMP-based EMS was proposed in Kim et al. (2011), who confined the optimal operating line of an ICE under a specific output torque and speed and also determined the appropriate equivalent battery usage parameters. In Yuan et al. (2013), a mathematical expression relating gear shifting to speed was established. A PMP-based EMS was proposed to transform the energy management issue into an optimal control problem based on the cost function. In Li et al. (2015), the fuel consumption, SOC, and battery loss were comprehensively considered for a harsh environment, and the SOC was restricted to a certain range. In addition, a battery operating severity factor was adopted to describe the loss status of the battery, and a PMP-based EMS was then proposed to reduce this factor. In Zhao and Antonio (2016), a PMP-based EMS was proposed and optimized using selective Hamiltonian minimization: a parameter analysis model was used to establish selective Hamiltonian minimization, and the selective Hamiltonian minimization was adopted to select the possible optimal control mode. In Hadj-Said et al. (2017, 2018), considering the discrete variables and continuous variables for PMP-based EMSs, the energy management problem was solved using an analytical method. The power distribution of the ICE and EM, the transmission ratio, and the start–stop process of the ICE were taken as the optimization variables.

Improving the real-time adaptability of PMP-based EMSs has become a hot research issue. In Lee et al. (2019), an adaptive PMP-based EMS established on real-time co-state adjustment according to the current driving conditions was proposed. Among the control process, the key control parameters were updated and balanced adaptively according to the SOC. In X. Li et al. (2019), an adaptive PMP-based EMS established on driving cycle prediction was proposed for fuel cell HEVs. The particle swarm optimization (PSO) algorithm was adopted to classify driving modes, and the Markov model was adopted to predict the speed and driving behavior in different driving modes. In Onori and Tribioli (2015), an adaptive supervisory PMP-based EMS was proposed to achieve online energy management of plug-in HEVs. Its co-state can be adjusted with changes in driving conditions. SOC feedback was used to eliminate the uncertainty in the average speed and total driving distance, and deviation between the actual SOC and the reference linear SOC distribution was prevented by resetting the co-state. The third necessary condition of PMP was only adopted in Nguyen et al. (2018) to derive a closed-form solution containing state variables in order to avoid EMSs relying on additional adaptive mechanisms in real-time control. In Xie et al. (2019), PMP and MPC were combined to realize short-term speed prediction using a Markov chain based on the actual driving cycle, and the EF did not need real-time adjustment; this was done with the aim of improving the calculation efficiency and real-time prediction performance.

The characteristics of different PMP-based EMSs are illustrated in Table 6. The PMP-based EMS improves calculation efficiency, but this method still cannot achieve real-time control. Under the premise of the certain constraint function and EF, the approximate global optimization solution can be obtained according to the vehicle model. The PMP-based EMS needs to work under a known driving cycle and cannot realize online control. Methods based on a predictive model and condition recognition are applied to this EMS. The PMP is used to solve the minimum energy consumption in the prediction domain in order to realize the near-real-time energy management of HEVs.

4.1.3 The GA-based energy management strategy

The GA was initially designed and proposed according to the law of biological evolution in nature. It obtained the optimal solution by simulating the natural selection in Darwin's evolution theory and the biological evolution process in the genetic mechanism. The GA uses mathematical methods and computer simulation to transform the optimization problem into a biology-like evolutionary process. In the GA, the fitness function is adopted to evaluate the merits and shortcomings of individuals. When the fitness of the optimization target reaches a set value, its fitness stops increasing, or the number of iterations reaches a set number, the GA optimization process stops, and the final optimization result is output (Lü et al., 2020). A flow chart of the GA is shown in Fig. 6.

The GA has been widely used in combinatorial optimization and adaptive control because of its simple form, good global optimization performance, and high calculation efficiency. The introduction of the GA provides a new method for solving energy management issues. In the energy management of HEVs, the fuel consumption, emissions, and vehicle performance are generally taken as fitness functions to achieve single- or multi-objective optimization.

$$\begin{cases} \min G = \beta_1 a_1(_1, x_2, \ldots x_n) + \beta_2 a_2(x_1, x_2, \ldots x_n) + \ldots \\ \qquad + \beta_k a_k(x_1, x_2, \ldots x_n) \\ \text{s.t. } b_i t(x) \le 0 \quad i = 1, 2, \ldots, p, \end{cases} \tag{11}$$

where G denotes the fitness; $x_1, x_2, \ldots x_n$ represent the optimized parameters; $a_1, a_2, \ldots a_n$ represent the fitness functions; $b_i(x)$ denotes the limiting conditions; and $\beta_1, \beta_2, \ldots \beta_n$ represent the weight of each fitness function.

In Panday and Bansal (2016), different battery models and SOC evaluation methods were adopted to analyze the vehicle performance, and a GA-based EMS was proposed, which can realize the optimization of the start–stop threshold of the ICE and SOC estimation algorithm. In Zhang et al. (2014), a GA-based EMS was proposed to transform the energy management issue into a multi-objective optimization problem including vehicle energy consumption, selected emission species, and the SOC. In addition, the variable domain method was adopted to transform the multi-objective problem into a nonlinear programming problem, which was solved using the GA. In Chen et al. (2014), an EMS combining the GA and quadratic programming (QP) was proposed, which simulated the relationship between the battery current and the fuel efficiency. The GA was adopted to search and optimize the start–stop threshold of the ICE, and QP was adopted to obtain the optimal battery current when the ICE was working. In T. Liu et al. (2018a), a GA-based EMS combined with condition recognition was proposed. The representative operating conditions of the four driving modes were obtained by classifying the historical driving data. The GA was adopted to solve and save the optimal control under different driving modes. The driving mode can be identified online, and the corresponding optimal control can be activated. In Zhan et al. (2016), an EMS based on the GA and the k-means clustering algorithm was proposed. First, four conventional driving modes were selected to obtain the relationship between the equivalent fuel coefficient and fuel consumption. The GA and k-means clustering algorithms were used to identify the driving modes, and the power distribution of the ICE and EM was adjusted in real time.

The characteristics of different GA-based EMSs are illustrated in Table 7. The GA provides a new idea for EMSs, allowing researchers to use the perspective of the vehicle itself. In addition, the GA also has strong adaptability and self-learning habit, which can produce a group of candidate solutions, deal with multiple individuals in the population, and search for various solutions in the space for comprehensive evaluation. However, for a GA-based EMS, there is no definite evaluation method with respect to its accuracy. In the calculation process, the GA is prone to premature convergence, which may affect the final result of the global optimization.

4.1.4 The GT-based energy management strategy

GT mainly studies the interaction between the formulaic incentive structures and is a mathematical theory and method to study competitive phenomena. GT considers the predicted behavior and actual behavior of individuals and studies their optimization strategies. At first, GT was used in economic activities. With the continuous progress of technology, GT has been gradually applied to military science, computer science, and other disciplines. The elements of GT are generally players, strategies, and gains and losses. We assume that the subject of the decision is entirely rational and aims to maximize their interests (Yin and Tian, 2010). GT can be described as an array, $(Z, m_i J_i : i \in Z)$ including the player Z, the strategies m_i, and the cost function J_i. The aim is to identify a range of strategies to satisfy the following:

Table 6. Summary of exemplary works on PMP-based EMSs.

Reference	Approaches	Application scenarios	Verification	Performance
Zhao and Antonio (2016)	PMP selective Hamiltonian minimization	HEV	Simulation	– Used the NEDC – The possible optimal control mode was selected using selective Hamiltonian minimization
Hadj-Said et al. (2017, 2018)	PMP Analytical method	Parallel HEV	Simulation	– Considered the discrete and continuous variables to realize the EMS using an analytical method – Optimization results were similar to the numerical method. – Improved the calculation efficiency
Wu (2018)	PMP Q-trick method	Series HEV	Simulation	– Used the NEDC – Transformed the EMS into a boundary value problem using Q-trick to simplify the calculation – Fuel consumption was 8.25 L per 100 km
Lee et al. (2019)	Adaptive real-time PMP	Extended-range electric vehicles	Simulation	– The control parameters were updated and balanced adaptively according to the SOC – Real-time co-state adjustment – Reduced driving costs by up to 13.5 %
Xie et al. (2019)	PMP MPC	Plug-in hybrid electric bus	Simulation	– Predicted speed using real driving cycles – Calculation speed was 6 times higher than DP – Comparable total cost to DP and PMP

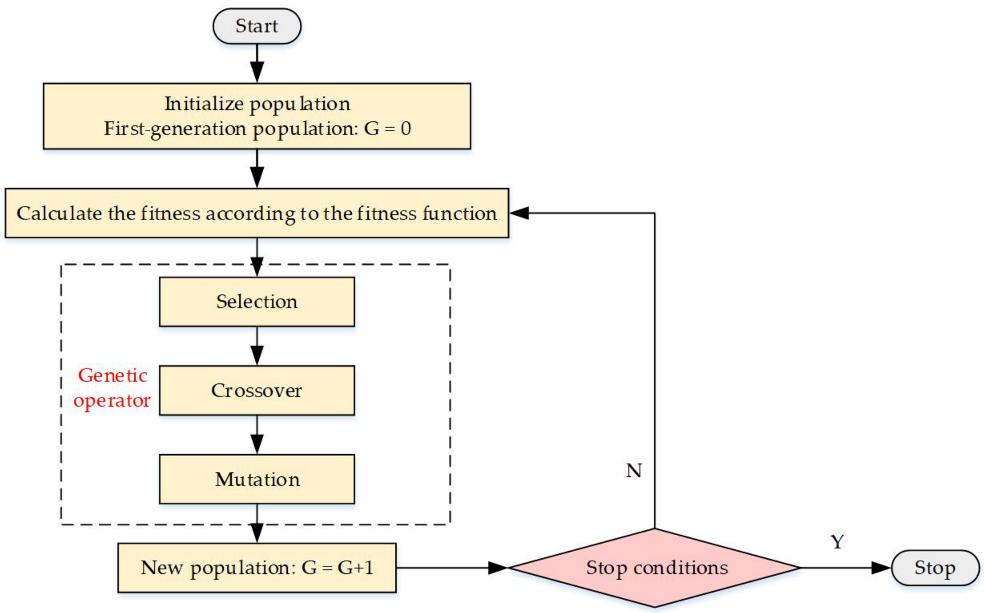

Figure 6. A flow chart of the GA.

$$
\begin{aligned}
& J_i\left(m_1,\ldots m_{i-1}, m_i^*, m_{i+1},\ldots m_n\right) \\
& \quad \geq J_i\left(m_1^*,\ldots, m_i^*,\ldots, m_n^*\right), \\
& \forall m_j \neq m_j^*, j \neq i, i=1,2,\ldots n.
\end{aligned} \tag{12}
$$

For HEVs, the players are the ICE, EM, and other power sources, and the common goal is to achieve the best fuel economy and power distribution. In addition, different power sources also have their own revenue goals. The propose of the ICE is to work in the high-efficiency range while reduc-

Table 7. Summary of exemplary works on GA-based EMSs.

Reference	Approaches	Application scenarios	Verification	Performance
Zhang et al. (2014)	GA Variable domain optimal	Parallel HEV	Simulation	– Multi-objective problem was transformed into a nonlinear problem using the variable domain optimal strategy – Balanced the energy economy, emission reduction, and the SOC stability
Chen et al. (2014)	GA Quadratic programming	Power-split plug-in HEV	Simulation	– The QP method was applied to calculate the optimal battery current when the engine was on – Also applicable when battery was degraded – Fuel consumption was reduced by 10.78 %
Panday and Bansal (2016)	GA SOC estimation algorithm	Plug-in HEV	Simulation	– The SOC estimation algorithm was applied to analyze the vehicle performance – Fuel economy was improved over classical methods
T. Liu et al. (2018a)	GA Driving condition recognition	Plug-in HEV	HIL	– Four driving modes were obtained by classifying the historical driving data – Applied in real time – Cost price was 46.6 % lower than the CD or CS modes

Table 8. Summary of exemplary works on GT-based EMSs.

Reference	Approaches	Application scenarios	Verification	Performance
Dextreit and Kolmanovsky (2014)	GT	Parallel HEV	Simulation	– Off-line calculation was simpler than SDP – Improved fuel economy and reduced emissions
Yin et al. (2016, 2018)	GT Adjustment program	Engine generator/ Battery/ Ultracapacitor HEV	Simulation Experiment	– Considered the life of each component – Adaptively adjusted the utility functions to improve the adaptability and the real-time performance
Xu et al. (2021)	GT Long short-term memory (LSTM) network	Hybrid energy storage system	Simulation	– LSTM network-based speed prediction – Feature extraction and time series analysis – Improved economy and prolonged battery life

ing emissions, and the propose of the EM is to keep the SOC within an appropriate range.

In Yin et al. (2016), a GT-based EMS was proposed for the hybrid power system composed of an ICE generator, a battery, and an ultracapacitor. Each respective part was taken as the player of GT, and energy management was realized while considering fuel consumption, battery protection, and charge–discharge capacity. Based on Yin et al. (2016), an adjustment program was added in Yin et al. (2018) that could adaptively adjust the weight of each part of the utility functions according to the output of each power source in order to improve the adaptability and real-time performance.

In Dextreit and Kolmanovsky (2014), a GT-based EMS was proposed, taking the driver's demand and the power system as two players, where cost penalizing referred to fuel consumption, NO_x emissions, SOC deviation, and vehicle running state deviation. The weight of the above parameters can also be adjusted appropriately. In Chen et al. (2015), an adaptive GT-based EMS was proposed to adapt to actual driving behavior. In this strategy, driving modes were predefined according to historical driving data. Each predefined driving mode had its corresponding probability distribution function. Different driving modes adopted different GT strategies to improve adaptability. In J. Xu et al. (2019), a GT-based EMS was proposed containing speed prediction trained using a recurrent NN (RNN) long short-term memory (LSTM) system based on 18 driving cycles. The speed prediction problem was selected to be treated as a multi-series problem to improve the accuracy. In Xu et al. (2021), a GT-based EMS established on prediction was proposed. Speed prediction was realized using a LSTM network. The feature extraction and time series analysis were adopted to improve accuracy. The prediction information was applied to a GT-based EMS to optimize the utility function of different power sources.

The characteristics of different GT-based EMSs are illustrated in Table 8. GT-based EMSs can guarantee good global optimization performance and better consider the performance requirements of each power source. Under the premise of no dependence on driving cycles or driving conditions, it can realize energy management and has strong robustness. In addition, the prediction module and real-time control module can also be added into GT-based EMSs to improve adaptability.

4.1.5 The CO-based energy management strategy

CO is a branch of the field of mathematical optimization, and the objective function is a convex function. Because the local optimization value and the global optimization value of CO are consistent, CO is simpler than the general mathematical optimization process in some aspects (Boyd and Vandenberghe, 2006).

The CO problem can be written as follows:

$$\begin{cases} p_0(x) \\ p_i(x) \leq 0, \ \ i = 1, 2, \ldots, m \\ q_j(x) \leq 0, \ \ j = 1, 2, \ldots, p \\ x \in \gamma, \end{cases} \tag{13}$$

where γ denotes the convex set, $p_i(x)$ denotes the convex function, $q_j(x)$ denotes the affine functions, and $p_0(x)$ denotes the objective function.

CO can transform the energy management problem of HEVs (such as the gear shifting, the start–stop process of the ICE, the charge–discharge of the battery, the power distribution, and other problems) into a semi-convex definite problem for solving, which significantly simplifies the calculation process while ensuring global optimization performance.

In Song et al. (2017), a CO-based EMS was proposed for a hybrid storage system. A linear approximate model of the composite hybrid storage system was established. The optimal parameters of each power source and corresponding EMS were solved using the CO method with the battery life and the cost of the hybrid storage system as the objectives. In Hadj-Said et al. (2016), a CO-based EMS combining the ICE on/off strategy was proposed. PMP was adopted to optimize the ICE on/off strategy to eliminate its non-convexity, and the corresponding analytical solution was obtained. The analytic solution was integrated into the EMS, and the torque distribution of the ICE and EM was solved using CO. In X. Hu et al. (2013), a CO-based EMS combining the CD and CS strategies was proposed for a plug-in hybrid electric bus. The torque of the EM, the SOC, the output power of the battery, and the ICE generator were set as the optimization objectives. In X. Hu et al. (2016), a CO-based EMS was proposed to optimize the emission characteristics of plug-in HEVs. This strategy can balance the battery output, the charging process, and ICE interactions. The goal of this EMS was to minimize the total amount of CO_2 emissions each day and to forecast and update the control process for the next day. In Nüesch et al. (2014b), a DP-optimized CO-based EMS was proposed that considered the influence of frequent ICE starting and stopping as well as frequent gear shifting. According to the driving cycle data, the optimal ICE on/off strategy and the gear-shifting strategy were solved by DP, which were transformed into a convex model. The energy management was then realized using CO. A novel heuristic method was proposed for optimal control, and an EMS was established based on CO and PMP in Murgovski et al. (2013). Only the start–stop process of the ICE was defined as an integer variable, and CO was used to solve the global optimization control. In Freudiger et al. (2020), a CO-based EMS was proposed for a hybrid storage system; this EMS took the power distribution as a decision variable, and CO was applied to reduce the total power loss. In Xiao et al. (2018), a CO-based EMS optimized using a simulated annealing algorithm was proposed. According to the speed and power demand, a convex function based on the fuel consumption of the ICE and battery power was established, and the battery power was controlled by CO.

The characteristics of different CO-based EMSs are illustrated in Table 9. The application of the CO method dramatically improves the calculation efficiency of EMSs. However, for CO-based EMSs, it is necessary to transform the optimization goal of the energy management issue into an appropriate convex model, and the constraint conditions must also be a convex model. For non-convex models, this method cannot solve the problem. Therefore, there are certain limitations in the application of CO, and it cannot meet the requirements of all energy management issues.

4.2 The instantaneous optimization energy management strategy

In research regarding instantaneous optimization EMSs, the ECMS-based EMS and the MPC-based EMS have been widely used. In addition, EMSs based on intelligent algorithms such as RL and NN have been gradually applied to HEVs. A comparison of these different methods is shown in Table 10, which illustrates the pros and cons of each method. This type of EMS was developed along with research into online control. The purpose of this strategy is to minimize the energy or power consumption at the current instantaneously,

Table 9. Summary of exemplary works on CO-based EMSs.

Reference	Approaches	Application scenarios	Verification	Performance
X. Hu et al. (2013)	CO CD/CS strategy	Plug-in hybrid electric bus	Simulation	– Improved the energy recovery efficiency – Considered the battery capacity – Explored the influence of battery capacity on energy consumption and efficiency – Diesel energy consumption was 8.87 MJ km^{-1}
Nüesch et al. (2014b)	CO DP	Pre-transmission parallel HEV	Simulation	– Considered engine start and gearshift costs – Fuel consumption was 0.1 %–0.2 % lower than DP – Calculation cost was 75 %–98 % less than DP
Xiao et al. (2018)	CO Simulated annealing	Parallel plug-in HEV	Simulation	– The fuel economy was 9.19 %–10.06 % lower than the CD/CS strategy – The calculation efficiency was drastically improved compared with DP
Freudiger et al. (2020)	CO	Extended-range HEV	Simulation	– DP was used as a benchmark – The total power loss of the whole system was reduced to a minimum

Table 10. A comparison of different methods applied to the instantaneous optimization EMS.

Approaches	Pros	Cons
ECMS	– Easy to implement – Online optimal control – Real-time implementation	– Relies on the selection of the EF – Less adaptability without an EF change – No global optimization control
MPC	– Strong robustness and stability – Feedback correction – Rolling optimization	– Relies on engineering experience – Less adaptability – Low calculation efficiency
RL	– High calculation efficiency – High adaptability – Independent of vehicle model	– Unknown influence of parameter selection – Ignores the optimization process – Low optimization performance
NN	– Independent of vehicle model – Real-time learning and updating – Back-propagation and feedback – High adaptability	– Relies on a large amount of historical data – Difficult to explain the process – High calculation cost

so that all parts of the HEV are in the optimal working state. This EMS is not restricted by the environment or driving cycle, and it has strong adaptability to unknown driving conditions, a fast response, and a low computational burden. However, this method cannot guarantee minimum energy consumption or emission during the whole driving cycle and cannot achieve global optimization.

4.2.1 The ECMS-based energy management strategy

The ECMS is an instantaneous optimization EMS with excellent performance in practical engineering applications. Its primary content mainly includes two parts: the first part is equivalent fuel consumption, which refers to the cost function established by converting the energy consumed or generated by the EM into the fuel consumption of the ICE using the EF, and the second part is instantaneous optimization, which takes the cost function as the optimization objective and solves the minimum value by adjusting the working state at each instantaneous moment. Therefore, the main problem of the ECMS is to establish a cost function (Jing, 2020). Parameters including battery health and the emission characteristics of the vehicle are also used as weighted terms in the cost function. This EMS can minimize the instantaneous energy consumption and adjust and optimize the working state and emission characteristics. Moreover, this EMS can be combined with various optimization methods to obtain multiple optimization effects. However, the selection of EFs often needs to be based on experience. The quality of EFs directly affects the adaptation of different working conditions.

In Jing et al. (2019), the SOC, the demand torque, and the EM speed were taken as input, and an ECMS-based EMS was proposed. In addition, the PSO algorithm was adapted to adjust EFs in real time to solve the optimal working point of the ICE and EM in order to realize the optimal energy distribution. In Khodabakhshian et al. (2013), an ECMS-based EMS was proposed in which the cost function included fuel consumption and the compensative electrical power consumption. A double variable function was established based on the SOC and its derivative to calculate the EF in the cost function. In Kommuri et al. (2020), an ECMS-based EMS was proposed for the best behavior assessment of HEVs. The battery aging, the start–stop process of the ICE, charging sustainability, and fuel economy were considered. The cost function was established, and instantaneous optimization was performed according to the working constraints of each component. In Nüesch et al. (2014a), an ECMS-based EMS established on the problem of excessive NO_x emissions from heavy-duty HEVs was proposed. This strategy introduced NO_x emissions into a cost function and tracked a given SOC reference trajectory in real time. In Qiao et al. (2019), an ECMS-based EMS was proposed for NO_x and particulate emissions that considered both fuel economy and emission characteristics. The cost function based on fuel economy and different pollutant emissions was established, and EFs of different pollutant emissions' influence on the cost function and optimization process were discussed.

With deepening research, a problem with the adaptability of the EF has been exposed. The fixed EFs cannot fully exploit the energy-saving advantages of HEVs. In order to adjust the EFs, an adaptive ECMS-based (A-ECMS) method has been proposed that can adjust control parameters according to current and future situation requirements. Its basic principle is to adjust the EF in real time according to the predictive model (Onori and Serrao, 2011). The commonly used methods to improve EMS adaptability include the SOC feedback, driving condition prediction, and speed prediction. Flow charts of these methods are shown in Figs. 7–9.

In Musardo et al. (2005), an A-ECMS-based EMS was proposed that combined the current and predicted speed and GPS data to establish the current driving condition. The EF was updated to realize the adaptive EMS. In addition, the ef-

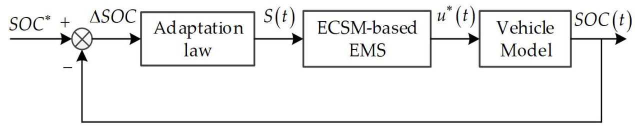

Figure 7. Flow chart of the SOC feedback control model.

fect of the updating frequency of the EF on the adaptability was also considered. In H. Liu et al. (2018b), an A-ECMS-based EMS was proposed based on target driving cycle generation for HEVs under fixed driving conditions. The co-state equation based on PMP was established, and the optimal solution under different initial SOC conditions was obtained. The adaptive cost function, composed of the fixed term and the dynamic term, was designed. The initial value of the fixed term was solved by the interpolation mapping of the initial SOC data and driving data, and the dynamic term was solved by PI (proportional integral) control according to the piecewise SOC reference curve. In Zhou et al. (2021), an A-ECMS-based EMS that integrated ramp information and the mass prediction was proposed. Combined with GPS data, the road slope was estimated, and the vehicle mass was estimated using the recursive least squares method. In addition, the reference trajectories of the SOC under different load conditions were established, and the traditional A-ECMS algorithm was used to track the reference SOC trajectories. In Li and Jiao (2019), an A-ECMS-based EMS established on traffic information recognition was proposed. The k-means clustering algorithm was adopted to divide the historical traffic data into four conditions. According to the current traffic conditions and the SOC, the EF corresponding to each typical traffic condition was solved. In Lei et al. (2020), an A-ECMS-based EMS considering traffic information was proposed. The GA solved the initial EF under different initial SOC conditions, and DP solved the optimal SOC trajectory. Fuzzy logic was used to adjust the EF in real time in order to track the optimal SOC trajectory. An ECMS was used to realize the optimal control. In P. Zhang et al. (2020), an A-ECMS-based EMS established on driving condition recognition was proposed. The driving conditions of heavy-duty HEVs were divided into six categories, and a driving condition recognition method based on NNs was proposed. The EF, the scale factor of a penalty function, and the start speed of the ICE were optimized using the PSO algorithm under each driving condition.

In addition, the combination of an ECMS-based EMSs and rule-based EMSs is very close. EMS control parameters are often optimized by rules, and the EF of the ECMS is adjusted within a certain range. In Vafaeipour et al. (2019), an EMS based on rules and the ECMS was proposed. The driving modes of HEVs were divided into five types using the "if else then" rule. The instantaneous power distribution was defined as a function of the SOC by the ECMS. In addition, the calculation results of the ECMS could also be used as the

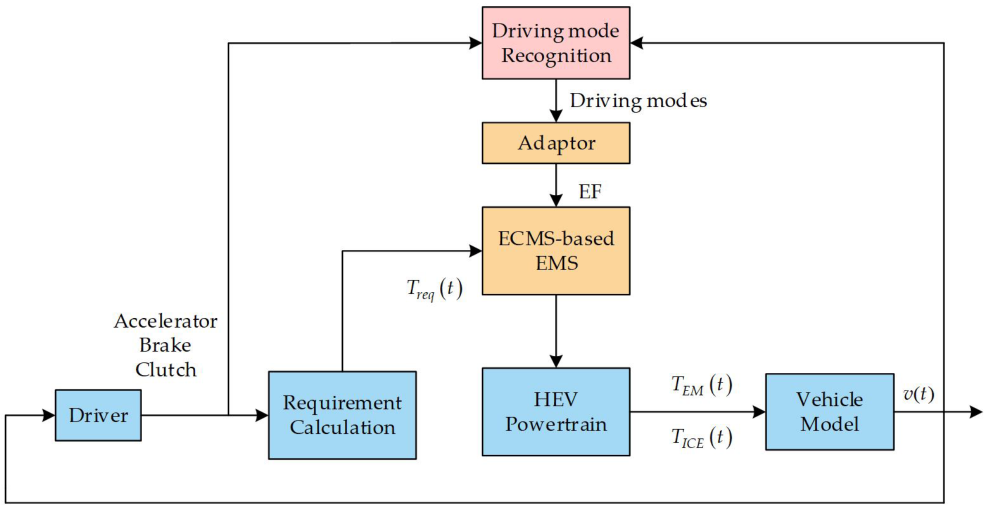

Figure 8. Flow chart of the driving condition predictive model.

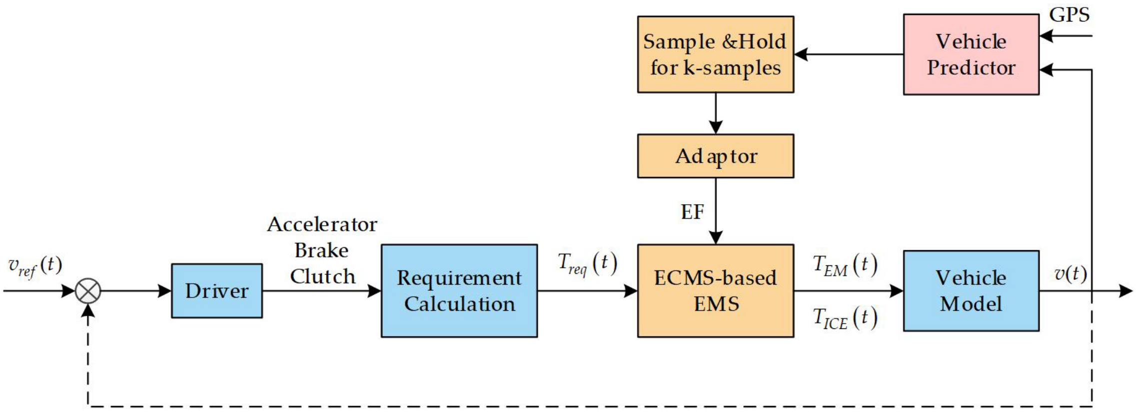

Figure 9. Flow chart of the speed predictive model.

basis for the division of driving modes. In Li et al. (2017), the rule-based method was used to divide the driving modes, and an ECMS-based EMS was adopted to optimize the energy management issue under hybrid driving conditions. In addition, PSO was used to solve the EF in real time in order to optimize the ECMS-based EMS. In Guercioni et al. (2020), an ECMS-based EMS combining a rule-based gear-shifting strategy was proposed. The optimal gear-shifting rule was obtained using DP, and the gear shifting was carried out according to the rule in the EMS. The torque distribution coefficient of the ICE and EM was optimized in real time. In S. Wang et al. (2019b), fuzzy control was combined with an ECMS-based EMS, and driver intention recognition was introduced into the EMS. Fuzzy control was used to adjust the EF according to the difference between the reference SOC and the actual SOC in order to obtain the optimal charge–discharge trajectory and ensure the continuity of the SOC. In Li et al. (2021), an online SOC estimation method based on a fuzzy inference system (FIS) and an adaptive updated traffic recognition method were integrated into an ECMS-based EMS. FIS was built by an adaptive neuro-FIS (ANFIS) trained by historical traffic data. The adaptively updated traffic recognition method and the estimated SOC value were applied to adaptively adjust the EF. In Liu and Zhang (2017), an ECMS-based EMS established on fuzzy logic driver behavior recognition was proposed. The fuzzy logic was used to identify different driver behaviors, and the EF was adjusted in real time according to the road information. The flow chart of this EMS is shown in Fig. 10. In F. Zhang et al. (2016), the difference between the reference SOC and its actual value as well as the derivative were the input, and fuzzy PI control was adopted to adjust the EF, which was applied to an ECMS-based EMS to improve the robustness, the SOC maintainable performance, and the fuel economy.

With the continuous development of computer science, many intelligent algorithms have been proposed and applied to ECMS-based EMSs; these algorithms are used to achieve adaptive adjustment of EFs and optimize the performance of

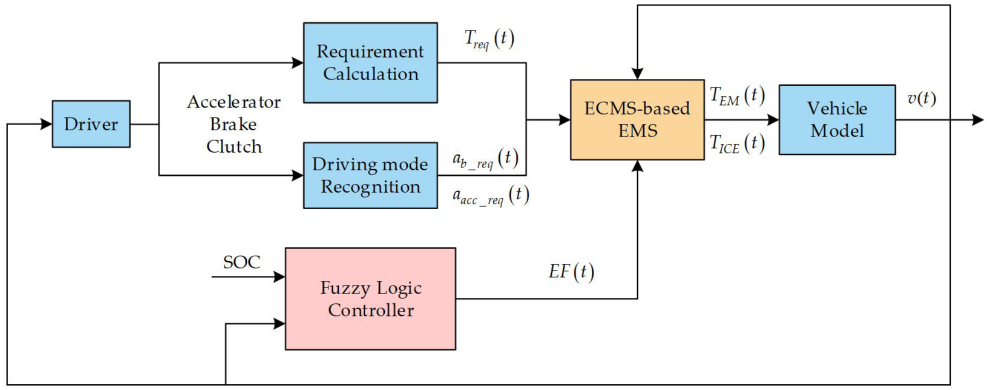

Figure 10. Flowchart of an ECMS-based EMS combined with fuzzy logic.

EMSs. In Wang et al. (2017b), an ECMS-based EMS established on PSO was proposed. The starting speed limit of the ICE was introduced, and the PSO algorithm was used to optimize the EF and the start speed threshold of the ICE under specific driving conditions. In Du et al. (2021), an ECMS-based EMS optimized using the PSO algorithm was proposed; this EMS added a penalty function and modified cost function according to the current SOC. In addition, the PSO algorithm was used to optimize the EF and penalty function of the battery charge–discharge. In Jing et al. (2019), an ECMS-based EMS established on the ant colony algorithm was proposed. The ant colony algorithm optimized the charge–discharge EF in ECMS to obtain the optimal charge–discharge EF off-line. In Li et al. (2018), the driving cycle identification of the k-means clustering algorithm was integrated into an ECMS-based EMS optimized using the GA. Characteristic parameters were extracted based on historical driving data, and driving conditions were divided into four categories. The relationship between different equivalent fuel coefficients and fuel consumption under four typical driving conditions was obtained using an ECMS to obtain the corresponding optimal power distribution. Based on KGA-means, the current driving condition was recognized. In Han et al. (2018), an ECMS strategy based on energy prediction was proposed. Energy prediction was estimated by the prediction velocity calculated by the chain NNs in different time layers. A novel adaptive rule has been developed by eliminating the need to reset the initial EF based on the energy prediction in order to adjust the EF in real time. In Tian et al. (2020), an ANFIS-optimized ECMS-based EMS was proposed considering the regularity and fixity of HEV driving conditions. The optimal control trajectory was obtained using DP, and a set of optimal EFs was obtained using the rolling optimization method, which was used to train an ANFIS. By using a trained ANFIS in the ECMS, the EF of the application was derived, and the online optimal power distribution was then realized.

The characteristics of different ECMS-based EMSs are illustrated in Table 11. Research regarding ECMS-based EMSs has experienced a transition from fixed EFs to variable EFs. The selection of the EF directly affects the optimal control performance of the EMS. The fixed EF was obtained according to experience or engineering data, representing all driving conditions. With the development of technology, more and more scholars have began paying attention to the adaptability of the EF and have began using different methods to describe the relationship between the EF and different driving conditions. Various intelligent algorithms and predictive models have also been introduced into EMSs to improve adaptability.

4.2.2 The MPC-based energy management strategy

MPC was a new control method. The basic principle of MPC is as follows: at each sampling moment, a finite domain optimization problem is solved according to the current information, and the obtained control sequence is applied to the controlled object. This process is repeated at each sampling moment, and the solution process of the optimization problem is constantly updated with new measured values (Huang et al., 2017). The four characteristics of MPC are as follows: the predictive model, the reference trajectory, rolling optimization, and feedback correction (F. Zhang et al., 2019). The principle and characteristics of MPC are shown in Fig. 11.

The MPC-based EMS transforms the optimization problem of the global condition into a local optimization problem in each predicted time domain. The rolling optimization continuously updates the driving state in the next predicted time domain. Because MPC has strong robustness and high stability as well as integrating rolling optimization and feedback correction, it is applicable to solve the HEV energy management problem with nonlinear multiple degrees of freedom (Morari and Baric, 2006).

In B. Zhang et al. (2019), an MPC-based EMS was proposed to achieve optimal power distribution and fuel consumption minimization. The driving modes of HEVs were selected using rules, and the optimization problem was solved using the sequential QP (SQP) method. In Chen et al.

Table 11. Summary of exemplary works on ECMS-based EMSs

Reference	Approaches	Application scenarios	Verification	Performance
Li et al. (2018)	ECMS KGA-means	HEV with CVT	Simulation	– Driving conditions identified by KGA-means – Overall fuel consumption reduced by 6.84 %
Qiao et al. (2019)	ECMS	P3 HEV	Simulation	– Considered energy consumption and emissions – Considered the influence of EFs of different pollutant emissions on the cost function and optimization results
Kommuri et al. (2020)	Modified ECMS	Parallel plug-in HEV	Simulation	– Considered the ICE start frequency and battery aging – Fuel benefit was 21.18 % (IDC) and 11.36 % (WMTC)
Lei et al. (2020)	A-ECMS	Plug-in HEV	Simulation HIL	– Adaptive correction of the EF using the fuzzy controller – Fuel consumption reduced by 6.01 % compared with the ECMS
P. Zhang et al. (2020)	A-ECMS	Hybrid heavy-duty truck	Simulation	– NN-based driving condition recognition – PSO-based EMS parameter optimization – Fuel economy improved by 14.81 % compared with the ECMS
Tian et al. (2020)	ECMS ANFIS	Parallel hybrid electric bus	Simulation HIL	– Optimal EF was produced by ANFIS online – Fuel economy improved by 18.42 % (CCBC) and 19.55 % (WVCITY) compared with rule-based EMS
Zhou et al. (2021)	Predictive ECMS	Hybrid mining truck	Simulation	– Road slope prediction based on GPS – Vehicle mass estimation – Fuel economy improved by 7.21 % compared with the traditional ECMS.
Li et al. (2018)	A-ECMS Fuzzy system	Plug-in HEV	Simulation	– Adjust EF online using traffic information and SOC estimation – Fuel consumption decreased by 22.98 % compared with rule-based EMS
Du et al. (2021)	ECMS PSO	Power-split HEV	Simulation	– EF and penalty function were optimized by PSO – Fuel consumption was 6.88 L per 100 km (WLTC) and 5.88 L per 100 km (NEDC)

IDC refers to the Indian Driving Cycle. WMTC refers to the World Motorcycle Test Cycle. CCBC refers to the Chinese typical City Bus drive Cycle. WVCITY refers to the West Virginia City Driving Schedule.

(2021), the demand power of HEVs was divided into high and low frequency, and an MPC-based EMS in the low-frequency band was proposed. The low-frequency power demand was taken as input, and the fuel economy, the SOC, and the busbar voltage were used as optimization targets. In Borhan et al. (2012), the energy management problem was first transformed into a problem considering the linear time-varying cost function. A quadratic cost function considering fuel consumption was then introduced into it, and an MPC-based EMS was subsequently proposed. The second cost function divided the fuel consumption into a stage cost and an approximation of "cost to go" as a function of the SOC. In Zhang and Shen (2016), the power distribution decision was regarded as a sublinear rolling optimization problem, and an MPC-based EMS was proposed. In addition, an online iterative algorithm based on a continuation/generalized minimum residual algorithm was adopted to solve the optimization problem. In C. Xiang et al. (2017a), two MPC methods were adopted to build an EMS according to the length of the sampling time. For a long sampling time, nonlinear

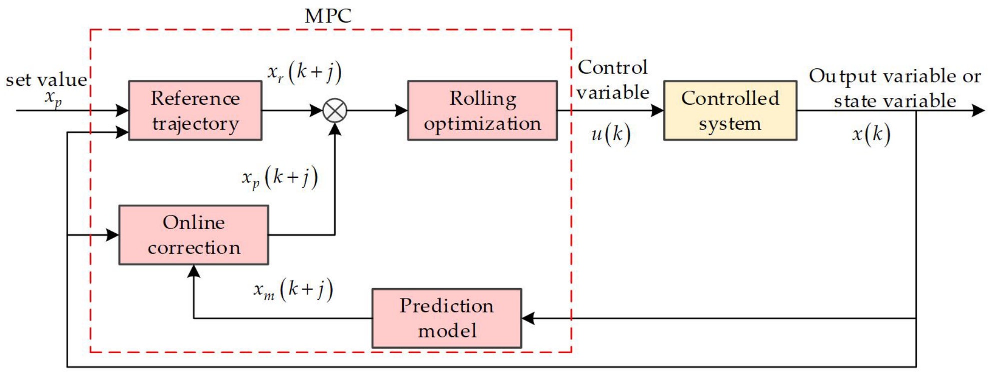

Figure 11. The principle and characteristics of MPC.

MPC was adopted to ensure the ideal SOC state and prevent significant ICE fluctuation. For a short sampling time, linear MPC was adopted to solve the optimization problem composed of the driving demands. In addition, the adaptive Markov chain was adopted to predict the load demand. In Cheng and Chen (2019), an MPC-based EMS was proposed to improve battery aging while also ensuring fuel economy. The fuel consumption, the SOC, and the battery aging index were predicted, and the cost optimization problem related to the above parameters was solved. In Luo et al. (2015), a multi-objective optimization control system was proposed for a new type of intelligent HEV, which used MPC to improve vehicle safety, fuel economy, and comfort; multistep DP was also used to solve the MPC off-line. In Zhou et al. (2017), a kind of MPC-based EMS was proposed for a hybrid storage system composed of a lithium battery and supercapacitor; this EMS could ensure that the system ran within the specified range and reduced the Ah throughput of the lithium battery. In this EMS, the predictive model was updated online, the model status was monitored in real time, and the QP method was used to obtain the optimal control in each solution interval. In Guo et al. (2017), an MPC-based EMS was proposed to divide the energy management problem into the optimal velocity trajectory and the torque distribution solution. The Krylov subspace method was used to solve the maximum velocity trajectory and improve the calculation efficiency. PMP and the numerical method were used to solve the optimal torque distribution and the gear-shifting rule.

Although MPC has a certain degree of robustness in solving uncertain problems, the method has certain limitations due to the fixed function. Scholars have proposed the stochastic MPC (SMPC) to solve these limitations, which included the probability of uncertainty in the optimization problem (Mesbah, 2016). In Qian et al. (2018), an SMPC-based EMS for four-wheel drive (4WD) HEVs was proposed. A Markov predictive model was applied to predict the acceleration and solve the demand torque. The rolling solution was carried out using DP to achieve the optimal control of fuel economy. In Xie et al. (2017), an SMPC-based EMS with a variable predictive time step was proposed to prevent the practical application interruption caused by driving state defects. A Markov predictive model was used to predict the velocity series, and average filtering and quadratic fitting were adopted to reduce the fluctuation in the predicted results. Online estimation and a variable threshold were adopted to predict the time variation in the time step, and SMPC was then used to solve the instantaneous optimal. In Cairano et al. (2014), an SMPC-based EMS was proposed combined with driver behavior learning based on the Markov model and a scenario-based approach for stochastic optimization and QP. According to the constraints of the SOC and battery charge and discharge power, SMPC was used to solve the optimal power distribution between the battery and the engine. In Li et al. (2016), an SMPC-based EMS based on “drive behavior aware” was proposed. The k-means algorithm was used to classify driver behaviors, and Markov models under different behaviors were established. When driver behaviors were regarded as random disturbances, an SMPC-based EMS optimized by the ECMS was used to eliminate some worsened fuel economy work points.

Scholars have added an intelligent algorithm-based speed prediction model, a road information prediction model, a driving condition prediction model, and q driver behavior prediction model to the traditional MPC-based EMSs to optimize their performance. In C. Xiang et al. (2017b), an EMS based on a nonlinear MPC (NMPC) was proposed that adopted a slow sampling time to maintain the SOC. In addition, a radial basis function NN was used to predict the short-term speed, and the optimal problem was solved using DP. In C. Sun et al. (2015a), the prediction accuracy, calculation cost, and fuel economy of an MPC-based EMS established on exponential variation was proposed. A random Markov chain as well as speed prediction based on NNs were evaluated to optimize the EMS. In Guo et al. (2019a), an adaptive MPC-based EMS was proposed. The SOC reference constraint of each MPC calculation step was obtained by solving the dynamic traffic information of the target driving task. In addition, the speed prediction model based on NN was used for short-term speed prediction, and the optimal energy allocation in the prediction domain was solved using DP within the framework of MPC. In Yang et al. (2020), an MPC-based EMS considering road ramp was proposed. The optimal speed was calculated based on the prediction of ramp information, and the power distribution and gear shifting based on MPC were then optimized based on the calculated speed. In Guo et al. (2019b), an MPC-based EMS established on ramp and speed prediction was proposed. A data-driven autoregressive integrated moving average model was applied to predict the future speed and road ramp of HEVs in real time in order to provide a reference for the speed and road ramp for the EMS, and this was used as input to solve the driving demands. In C. Sun et al. (2015b), an MPC-based EMS established on real-time traffic data prediction was proposed. The traffic prediction information could be used to establish the average speed of the current section and solve the SOC reference trajectory, which could be applied as the constraint condition of the SOC. In Park and Ahn (2019), an MPC-based EMS established on future driving cycle prediction was proposed. The radar signal and vehicle operation signal were used as input, the future driving cycle was predicted by deep NN, and the predicted near-future driving cycle was used as input to solve the optimal energy distribution.

The characteristics of different MPC-based EMSs are illustrated in Table 12. MPC-based EMSs can efficiently solve the optimization problems with multivariable constraints and can also overcome the uncertainty of the system to a certain extent, due to strong robustness and stability. The introduction of SMPC can avoid the influence of random constraints to a large extent and further improve the adaptability of the control system. In addition, a variety of prediction-based methods have been introduced into EMSs and can improve their adaptability to unknown driving conditions. However, multiple optimization goals often need to be considered. The mutual restriction and influence of various performance indicators will inevitably introduce more constraints. It is still a difficult point for intelligent algorithms to optimize the calculation process and ensure real-time performance. In addition, in the complex road environment, the randomness of human–vehicle–road interaction will also affect the control performance of MPC.

4.2.3 The RL-based energy management strategy

RL is a method used to describe and solve an agent's interaction process with the environment in order to achieve the maximum return or a specific goal. It has been developed from animal learning and parameter disturbance adaptive control theory and is currently applied in automatic control. RL uses a framework to define the interaction between the agent and the environment in terms of state, action, and reward (Sutton and Barto, 1998).

RL has obvious advantages in dealing with uncertainty problems and can realize the optimization process through training. In HEV energy management problems, action is generally defined as control variables in EMSs, such as the speed, the torque of the ICE and EM, and other parameters. The state is the real-time working state of all parts of the HEV in operation, such as the speed, the SOC, and the current driving conditions. The reward function is the final control goal that needs to be achieved, including the fuel economy, the SOC stability, the battery health, and the emission characteristics (X. Hu et al., 2019). A schematic diagram of an RL-based EMS is shown in Fig. 12.

In Zou et al. (2016), an RL-based EMS for a hybrid tracked vehicle was proposed, and a control-oriented hybrid tracked vehicle model and a power demand model were established. A recursive learning algorithm for power demand transfer probability matrices (TPMs) established on the Markov chain was proposed based on historical data. The Kullback–Leibler divergence rate was applied to measure the difference in power demand TPMs. When the difference was significant, the RL-based EMS was updated in real time. In Xiong et al. (2018), aiming at the optimal power distribution problem between the battery and supercapacitor in a hybrid storage system, an RL-based EMS that judged and updated according to the Kullback–Leibler divergence rate was proposed. The power TPM was solved using long-driving-period data. A control strategy based on a reverse learning algorithm was established, and the TPM was updated according to the applied driving cycle. In Sun et al. (2020), according to the ECMS principle, a data-driven RL-based EMS was proposed. An optimization problem with the SOC retention and fuel consumption as objectives was established. The EMS was simplified by an adaptive fuzzy filter. In Liu et al. (2020), a double-layer adaptive RL-based EMS was proposed. The upper layer calculated the corresponding TPMs according to the drive cycle change, and the induced matrix norm was adopted as the standard to identify the transformation. The lower layer was based on the model-free RL and used the transformed TPMs to solve the optimal power distribution. In Hu et al. (2018), an EMS based on deep RL (DRL) was proposed for adaptability to different driving conditions. The reward function was directly related to fuel consumption. The EMS adopted the QNN (Quantized Neural Networks) online learning method to obtain the action from the state and to realize the identification and conversion of driving conditions. In order to solve the problem of the large control variable space in the EMS, the battery performance and the optimal brake specific fuel consumption curve of the HEV were introduced into the DRL-based EMS in Lian et al. (2020). The state parameters and optimization parameters based on the HEV itself can ensure training accuracy. In B. Xu et al. (2019), an RL-based EMS established on Q-learning was proposed. The EMS took the speed and demand torque as the state of Q-learning, chose the demand torque of the EM as the action, and the reward function included the fuel consumption of the ICE and the equivalent battery fuel consumption. During the actual driv-

Table 12. Summary of the exemplary works on MPC-based EMS.

Reference	Approaches	Application scenarios	Verification	Performance
Li et al. (2016)	SMPC *k*-means	Plug-in hybrid electric bus	Simulation	– Driver behavior classification and prediction – ECMS used to modify the SMPC – Fuel consumption reduced by 26.61 % compared with the CD–CS modes and by 5.58 % compared with single SMPC
Qian et al. (2018)	SMPC	4WD HEV	Simulation HIL	– A Markov chain was built to describe changing acceleration – Fuel economy improved by 5.51 % (NEDC), 6.87 % (UDDS), and 15.02 % (CUDS) compared with frozen-time MPC
Cheng and Chen (2019)	NMPC	Power-split HEV	Simulation	– Considered the battery aging – The state of health over a single driving cycle improved by 0.09 %, 0.25 %, and 0.44 % under different EFs – Similar fuel economy to a single NMPC
Guo et al. (2019a)	MPC DNN	Plug-in HEV	Simulation HIL	– DNN-based speed prediction – Integrated economy driving pro system – Fuel economy improved by 6.48 % compared with an EMS without EDPS
Guo et al. (2019b)	MPC ARIMA	Power-split HEV	Simulation	– ARIMA-based road gradient and velocity prediction in the short term – The ARIMA model was established based on real driving cycle and road gradient data – Fuel economy increased by 5 %–7 %
Park and Ahn (2019)	MPC DNN	Parallel HEV	Simulation	– Radar signals from the ego vehicle were used as the input for the DNN – DNN-based duty cycle prediction
Yang et al. (2020)	Hierarchical MPC	Parallel HEV	Simulation	– Obtained the optimal velocity using the road slope ahead – Optimized the power split and gear ratio using MPC – Fuel economy was 25.6 % higher compared with the EMS not considering road slope

CUDS refers to the China Urban Driving Schedule. EDPS refers to the Economy Driving Pro System.

ing process, the Q-value table would be updated adaptively every time. In T. Liu et al. (2018b), an RL-based EMS established on speedy Q-learning was proposed, which adopted the real-time learning model to calculate the TPMs of power demand under different driving conditions and also distinguished the TPMs using the induction matrix norm. In addition, the speedy Q-learning algorithm was adopted to accelerate the calculation convergence speed of the Markov chain. In Han et al. (2019), a double deep Q-learning-based EMS was proposed to optimize the energy management problem while maintaining the stability of the SOC. In addition, double deep Q-learning was used to correct the error caused by the overestimation of the cost function. In Xu et al. (2020), it was proposed that the effectiveness of an RL-based EMS largely depended on the selection of optimization parameters. Thus, this paper explored the aspect of EMSs caused by the number and selection of states, the discretization of states and actions, and the selection of the learning experience. The results showed that increasing the discretization of states will decrease the fuel economy, whereas increasing the discretization of actions will increase the fuel economy.

The characteristics of different RL-based EMSs are illustrated in Table 13. As a model-free control method, RL-based EMSs have been widely used in HEV energy management in

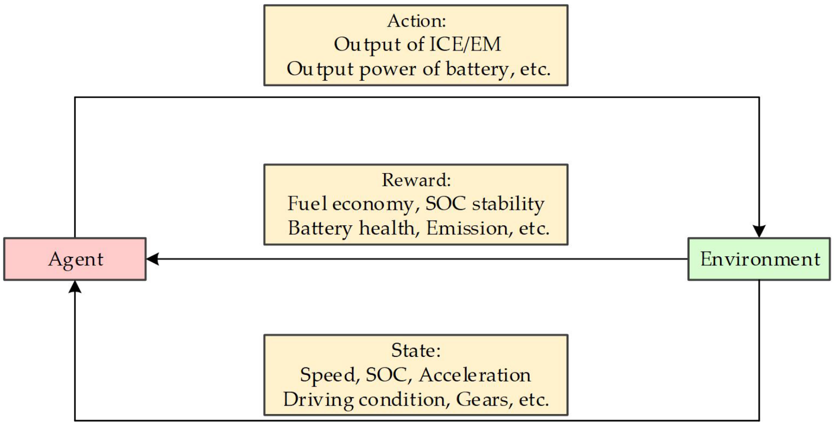

Figure 12. A schematic diagram of an RL-based EMS.

Table 13. Summary of exemplary works on RL-based EMSs.

Reference	Approaches	Application scenarios	Verification	Performance
Zou et al. (2016)	RL Recursive learning algorithm	Hybrid tracked vehicle	Simulation	– Used a user-defined cycle – A recursive learning algorithm for power demand TPMs established on a Markov chain was proposed based on historical data – Improved fuel economy by 1.53 %
Xiong et al. (2018)	RL	Plug-in HEV	Simulation	– Updated the EMS according to the Kullback–Leibler divergence – The relative decrease in total energy loss could reach 16.8 %
Hu et al. (2018)	DRL Deep NN	Plug-in HEV	Simulation	– Obtained action directly from the states by QNN online learning – Fuel consumption of the DRL-based EMS trained under NEDC online was 3.478 L km^{-1}
T. Liu et al. (2018b)	RL Speedy Q-learning	Hybrid tracked vehicle	Simulation	– Used two user-defined cycles – Fuel consumption was 2821.3 g per driving cycle and 5.57 % lower than SDP. – High calculation efficiency
Han et al. (2019)	Double deep Q-learning	Hybrid tracked vehicle	Simulation	– Used a user-defined cycle – Fuel consumption was 23.5 L km^{-1} – Fuel economy was 7.1 % better than DQL
Lian et al. (2020)	Rule-interposing QRL	Toyota Prius	Simulation	– Fuel consumption was reduced by up to 4 % – The simplified action space improved the convergence efficiency by 70.6 %

QRL denotes Q-reinforcement learning. DQL denotes deep Q-learning.

recent years due to their good adaptability to different driving conditions and high calculation efficiency. However, there are still major problems with selecting parameters for this type of EMS, and the effect of different parameters on the RL framework is still unknown. In addition, RL needs to be trained according to a large amount of data and constantly updated in the application. Although RL can achieve instantaneous optimization, its optimization performance is not as excellent as other EMSs. Therefore, it is necessary to add constraints based on vehicle information into the RL framework to carry out optimization.

4.2.4 The NN-based energy management strategy

An NN is an adaptive information processing system based on the interconnection of many processing nodes. Models of the human brain are built from information processing, and networks are formed according to certain connections. The NN is composed of many connected nodes, and each node represents an activation function. An NN has strong self-adaptability and self-learning functions that can learn and update in real time according to changes in the system (Dougherty, 1995). NNs are generally divided into an input layer, a hidden layer, and an output layer. The topology and weights determine the performance of an NN. The topological structure ensures strong nonlinearity. The weights need to be trained by NNs based on large amounts of data. In addition, the NN also has the function of back-propagation, which can reduce the final output error by comparing the output value with the target value to solve the error and reverse input (Baumann et al., 1998).

In NN-based EMSs, parameters such as the current vehicle speed, the SOC, output information from the EM and ICE, and demand torque are generally taken as the input layer. In contrast, the output layer is generally the optimization target, including the optimal power distribution, fuel consumption, equivalent fuel consumption, and emissions of the HEV. In addition, this type of EMS is trained based on a large number of historical data collected under various driving conditions. The network is constantly updated and optimized for practical use. The control structure diagram of an NN-based EMS is shown in Fig. 13.

In Tian (2018), an NN-based EMS was proposed for a hybrid electric bus under fixed driving conditions that took the demand torque, speed, SOC, and mileage ratio as input and obtained the optimal power output of the ICE. Due to the continuous accumulation of determined conditions, the obtained optimal data set for NN training was also increased. In Majed et al. (2016), an NN-based EMS was proposed for a fuel cell HEV. In this strategy, the driving demands of the HEV were firstly predicted, and the predicted results, the SOC, and the fuel cell power were taken as the inputs for the NN. In addition, the optimal results obtained by DP were used for off-line training of the NN. In Q. Xu et al. (2018b), an NN-based EMS was proposed based on the principle of minimum power loss. This strategy took the demand torque, speed, and SOC as the input layer, and the output power of the ICE and the speed were obtained after calculating the hidden layers. Considering the efficiency of the transmission system of a dual-mode HEV, an NN-based EMS was proposed in Qi et al. (2015). The GA was applied to train the weights of the NN. Based on the transmission efficiency model, the optimal control strategy of the ICE speed was established and integrated into the EMS. In Ates et al. (2010), an NN-based EMS combined with a wavelet transform was proposed for a fuel cell/ultracapacitor hybrid storage system. Wavelet transform was used to reduce the power fluctuations in fuel cells and keep them in a steady state, while NNs were used to control the charge depletion of the ultracapacitor. In Wang and Qin (2020), the ECMS strategy was integrated into the BPNN-based EMS. The EF was used as the intermediate variable to solve the global optimization sequence, and BPNN was then used to extract the optimal sequence and form an online EMS. In Han et al. (2020), an RNN-based EMS was proposed. This strategy could adjust the ratio of energy consumption and battery loss in the EMS in real time. The SOC trajectory was calculated using DP for training. It could also control the deviation between the training value and the actual value in a practical application. In Kong et al. (2019), an EMS based on deep RNN (DRNN) was proposed. Multiple parameters related to the current driving condition of the HEV were selected as inputs, and the optimal output torque of the ICE was obtained through the hidden layers. In addition, the weights in the hidden layers were updated in real time. In Chen et al. (2020), an EMS based on convolutional NN (CNN) was proposed for condition identification. This strategy divided the conventional driving conditions into six types using the K-shape clustering method, and the CNN was trained based on the initial driving cycle and forecasted the driving conditions. In Zhang and Fu (2020), an EMS based on fuzzy logic and an NN was proposed to improve the adaptability of EMSs to different driving conditions. The EMS realized the identification of driving cycles through the sample learning and feature extraction of the NN and used it as the input for the fuzzy logic controller to optimize the MF. In Wu et al. (2020), an EMS based on multi-NNs was proposed. The global optimization results were obtained using DP, the condition recognition NN was trained by the calculation results, and the online co-state estimation was realized using RNN, which was used as the initial value of battery power optimization.

The characteristics of different NN-based EMSs are illustrated in Table 14. The NN-based EMS is a model-free control strategy with a strong learning ability that can deal with the nonlinear optimal energy management problem in real time. It can optimize and update the control process to realize the self-adaptation of the algorithm itself. However, it is difficult to explain the reasoning process of an NN, and the calculation cost is high. In addition, in the case of insufficient data, the NN-based EMS finds it difficult to achieve the optimization effect. Therefore, an NN is often used in combination with other algorithms to form a multi-method control system, which integrates the self-learning performance of an NN into the adaptive EMS to obtain better adaptability.

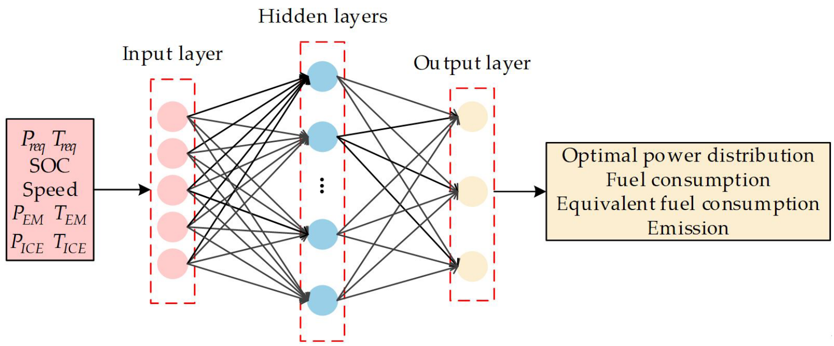

Figure 13. The control structure diagram of an NN-based EMS.

Table 14. Summary of exemplary works on the NN-based EMS

Reference	Approaches	Application scenarios	Verification	Performance
Majed et al. (2016)	ANN	Fuel cell HEV	Simulation	– The ANN was trained using UDDS – The effect of HWFET was better than NEDC – The system cost was 1.2 % lower than DP
Kong et al. (2019)	DRNN	Parallel HEV	Simulation	– Hidden layers were updated in real time – Equivalent fuel consumption was 7.52 L per 100 km (CYC_1015) and 5.6 L per 100 km (NDEC UDDS)
Wang and Qin (2020)	BPNN A-ECMS	Plug-in HEV	Simulation	– Optimal EF recognition – The fuel economy was improved by 2.46 %
Han et al. (2020)	RNN A-ECMS	Plug-in HEV	Simulation	– Adjusted the ratio of energy consumption and battery loss in real time – Considered the battery life
Zhang and Fu (2020)	NN Fuzzy logic	Parallel HEV	Simulation	– Fuel consumption was 5.576 L km^{-1} (NEDC) and 6.096 L km^{-1} (FTP-75) – Optimization ratio was 21.39 % (NEDC) and 31.85 % (FTP-75) compared with the fuzzy EMS
Wu et al. (2020)	Multi-NN	Hybrid electric mining truck	Simulation	– Radial basis function NN-based speed prediction – The cost savings were 12.2 %–34.68 % – The computation time decreased by 23.40 %

CYC_1015 represents the Japanese 10–15 mode driving cycle. NDEC represents the New European Driving Cycle.

5 The EMS based on intelligent transportation systems

The ITS refers to the transportation environment in which vehicles, infrastructure, and portable devices are interconnected. It effectively applies information technology and sensor technology in transportation to strengthen the connection between vehicles, roads, and people, thereby forming a real-time, efficient, and accurate transportation system. However, the main problems faced by the ITS with respect to its development include comprehensive access to the traffic status, an accurate understanding of vehicle running conditions and the behavior of other traffic participants, and the provision of more effective traffic information according to vehicle traffic conditions and the related states of mutual interaction (Peng, 2019). The architecture of the ITS is shown in Fig. 14.

The introduction of "Internet of Vehicles" (IoV) technology can solve these problems to a large extent. IoV refers to the system network of data exchange between vehicles, roads, and people based on the internal network, inter-vehicle network, and onboard mobile network through radio frequency identification (RFID) technology, which can realize the integrated control of traffic management and vehi-

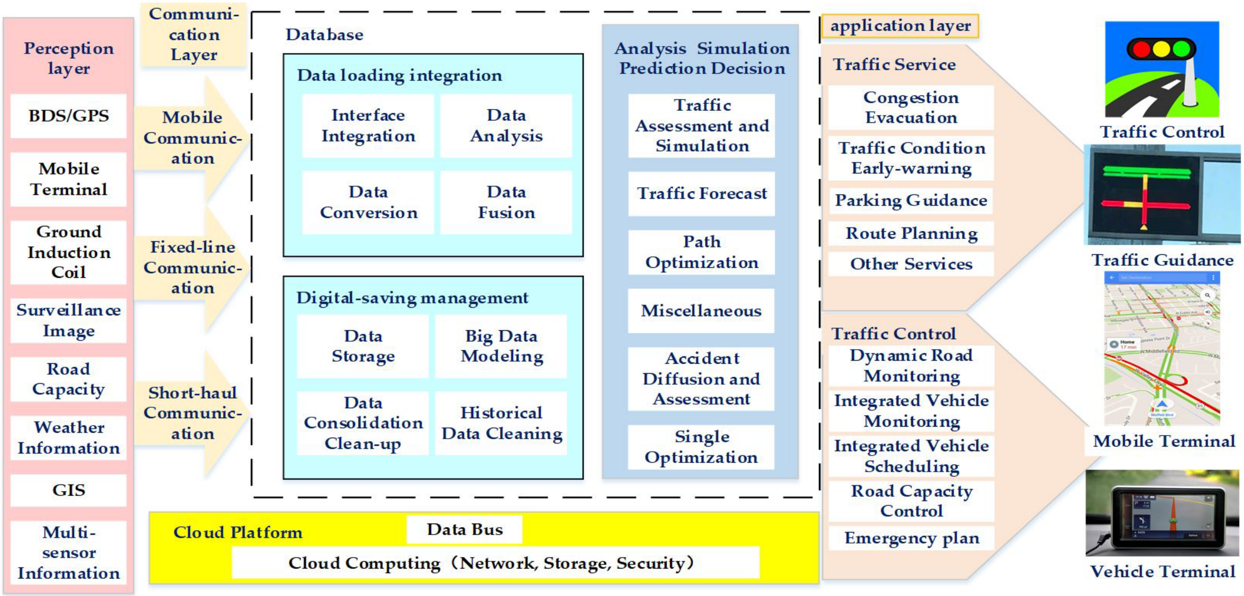

Figure 14. The architecture of the intelligent transportation system (ITS).

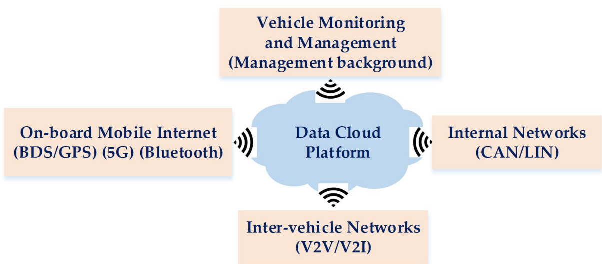

Figure 15. The architecture of IoV.

cles (Yang et al., 2014). The architecture of IoV is shown in Fig. 15.

With the continuous development of the ITS and IoV technology, the application of intelligent traffic data information to the optimization control of HEV energy management has become a hot topic for scholars (Gu et al., 2019). Generally speaking, ITS-based EMSs use two methods: the first method is based on using static data (e.g., navigation information and historical traffic data) to predict driving conditions in the predicted time domain to realize energy management, whereas the second method is to monitor and predict the behavior of nearby vehicles, traffic signals, and traffic participants according to the dynamic real-time traffic information provided by IoV in order to find the optimal speed to achieve energy management.

5.1 ITS-based EMSs established using static data

ITS-based EMSs established using static traffic data usually classify different driving condition data based on vehicle historical driving data, navigation information and GIS information, and they use an adaptive algorithm to predict the future driving state in the time domain, thereby realizing energy management in the prediction domain. This method mainly adopts the idea of hierarchical control. The upper layer is the classification and prediction layer, which classifies the driving conditions of vehicles according to the historical data and also predicts the driving parameters and driving conditions of the current vehicles. The lower layer adopts the corresponding EMS according to the prediction results to realize the optimal energy allocation of vehicles

In Wei et al. (2016), driving pattern recognition (DPR) was introduced into the ITS-based EMS. The fuzzy rule was designed based on the DPR algorithm that determines the current driving mode based on the historical vehicle data in the upper layer, and fuzzy logic was applied to solve the energy management problem. While driving conditions changed frequently, the MF was adjusted according to DPR results. In R. Zhang et al. (2019), multilayer perceptual NNs were used to extract the features of historical driving conditions to realize the DPR, which was introduced into the ITS-based EMS. Under different driving conditions, the optimal power distribution was realized by fuzzy control. In addition, the GA was used to optimize the critical parameters in the MF, which can reduce the current fluctuation under various driving conditions. In Zhang and Xiong (2015), an ITS-based EMS established on DPR was proposed that used fuzzy logic to divide and identify current driving modes according to the historical information from the last 100 s. An optimal EMS was then developed using DP in order to realize real-time adaptive energy management. In Kim et al. (2019), an ITS-based EMS with DPR was proposed for HEVs with repeated driving conditions, as it can update control parameters in real time by analyzing the past driving modes. The trip information was also updated every day to optimize the DPR. The effective average power and the effective SOC drop rate were selected to determine the driving mode. In the lower layer, PMP was applied to obtain the optimal control results. In C. Wang (2020), an ITS-based EMS was proposed in which the current driving condition was predicted according to the historical driving condition data. According to the predicted driving condition, the GA was applied to solve the energy management issue with the gear-shifting model. The vehicle fuel consumption was taken as the fitness function to avoid the influence of multiple EFs. In Rios-Torres et al. (2018), the diving conditions of HEVs were divided into volatile, normal, and calm according to historical driving data, and an ITS-based EMS was then proposed. In addition, the driving conditions were estimated using real-time vehicle operating parameters. The current driving condition was determined, and ECMS was applied to reduce fuel consumption. Under calm conditions, fuel consumption was reduced by 13 %. In Sun et al. (2016), an ITS-based EMS established on speed prediction was proposed. The prediction of the future short-term driving condition was realized using NNs speed prediction and historical data. A-ECMS was applied to realize the adaptation of EFs by the prediction results, and the driving behavior was then adjusted. In Haußmann et al. (2019), an ITS-based EMS established on driving behavior recognition was proposed. The learning method was used to classify the historical driving data, and the driving conditions were divided into four categories. LSTM-RNN was used to identify driving behaviors online and select the corresponding optimal driving mode based on driving parameters such as speed, acceleration, and braking distance. The optimal power distribution was obtained using the ECMS. In Lian et al. (2017), an ITS-based EMS combining speed prediction based on identifying driving intention and historical driving speed was proposed. A nonlinear autoregressive NN was used to predict the speed, and the demand torque was then predicted. Following this, a mixed logical dynamical model was established to obtain the optimal power distribution within the predicted speed range. In Wang et al. (2020), an ITS-based EMS driven by a large amount of historical driving data was proposed, and the DRL framework was applied to realize the optimal power distribution trained by the large-scale HEV driving conditions. The reward function was established to minimize fuel consumption and power consumption while maintaining power stability. In H. Liu et al. (2018a), an ITS-based EMS established on radial basis function NN speed prediction was proposed. The ramp information from GIS was applied to plan the SOC trajectory in real time. The predicted speed and SOC trajectory were used as the input for the EMS. In the framework of MPC, the energy management problem was solved, fuel economy was improved, and the SOC was maintained in real time. According to the influence of ramp on EMS, an ITS-based EMS established on slope prediction was proposed in Zeng and Wang (2015). According to the driving condition and terrain information, the predictive model of road ramp based on the Markov chain was established. In the optimal layer, the SMPC and SDP were applied to realize the energy management according to the SOC and the ramp prediction model. In Wu et al. (2008), an ITS-based EMS was proposed combined with the BPNN. The energy management rules obtained by a road condition information off-line simulation were introduced into the EMS. The fuzzy c-means cluster was applied to classify the rules. The rules were used to train the NN in order to obtain the optimal ICE output.

The characteristics of different ITS-based EMSs established using static data are illustrated in Table 15. This type of EMS can realize efficient energy management of vehicles in the prediction domain. It can integrate the characteristics of various driving conditions and combine the advantages of a large number of historical data to train the EMS optimization process with the formation of an approximately optimal control process. In addition, the integration of geographic information and navigation information can improve the prediction performance of the driving path to a certain extent and adjust the EMS according to the actual road condition information to improve the control effect.

However, this EMS is highly dependent on the prediction accuracy, and the prediction effect of different prediction algorithms is also different. When the prediction effect is not close to the actual driving process, the vehicle energy management effect may not be optimal. Therefore, the key to this EMS is to select a suitable prediction method to improve the prediction accuracy.

5.2 The ITS-based EMSs established using real-time data

ITS-based EMSs established using real-time traffic data involve the optimal power distribution of the vehicle driving system and include the autonomous planning of the vehicle running state by the target vehicle according to the specific driving environment. This method also mostly adopts the idea of hierarchical control. In the upper layer, the speed optimization method is put forward according to the signal phase and timing (SPAT) and the vehicle running status information. This is to avoid the vehicle being in the frequent deceleration and stop position and to ensure that the vehicle is in the high-efficiency running speed range (Wang, 2020). In addition, according to the speed optimization results in the lower layer, the corresponding optimization method is used to realize the optimal power allocation, and the fuel economy of the HEV can be improved.

In Qian et al. (2017), an ITS-based EMS was proposed according to the signal light information under the ITS framework; this strategy improved fuel economy by avoiding the HEV having to stop at a red light. SPAT was used to calculate the velocity range of the target, and F-MPC was then used to calculate the optimal velocity sequence at a given

Table 15. Summary of exemplary works on ITS-based EMSs established using static data.

Reference	Approaches	Application scenarios	Verification	Performance
Wei et al. (2016)	Historical data Fuzzy logic DPR	HEV	Simulation	– Used the UDDS driving cycles – Driving condition recognition and division – Fuel consumption reduced by 3.85 %
H. Liu et al. (2018a)	GIS NN MPC	Parallel HEV	Simulation	– NN-based speed prediction – Planned the SOC trajectory using GIS ramp data – Updated the predicted speed and SOC trajectory in real time
R. Zhang et al. (2019)	Historical data Fuzzy logic GA NN	Fuel cell/ Supercapacitor HEV	Simulation	– NN-based DPR – Critical factors of the MF were optimized using the GA – Ensured that the SOC of the supercapacitors is within the desired limit
Kim et al. (2019)	Past driving modes PMP	Plug-in HEV	Simulation	– Updated the control parameters in real time by analyzing past driving modes – Used the effective mean power and SOC drop rate to determine the driving patterns
Rios-Torres et al. (2018)	GPS-based driving record ECMS	HEV	Simulation	– Combined driving cycles with driver decision – Driving condition recognition and division – Fuel consumption reduced by 13 % under calm conditions

time. According to the optimal speed sequence, energy management is realized using the ECMS based on the Willan line method. In Qian et al. (2016), an ITS-based EMS established on vehicle-to-vehicle (V2V) communication and vehicle-to-infrastructure (V2I) communication was proposed. The optimal target velocity was obtained by SPAT, multi-island GA, and NMPC. An A-ECMS was used to determine the optimal energy distribution and obtain the optimal output power of the ICE and EM, which could improve fuel economy while avoiding the shutdown of the HEV due to red lights. In X. Qi et al. (2017), an ITS-based EMS was proposed that divided the optimal speed curve of HEVs passing the signal light into four working conditions according to the SPAT. The appropriate working condition curve was selected according to the actual running state of the vehicle, and the demand power of the vehicle in the running process was predicted by MPC. The CD–CS strategy was used to solve the energy management problem. In F. Zhang et al. (2017), an ITS-based EMS established on future vehicle speed prediction was proposed. According to the real-time traffic information provided by V2V and V2I, a CNN was used to predict the speed in different time ranges, and the ECMS was used to achieve energy management. In addition, the effects of predicted speed on the EF and fuel economy were considered, and the EF was adjusted adaptively. In Gong et al. (2008), historical traffic information and a real-time traffic signal sequence based on the ITS were applied to travel modeling, and an ITS-based EMS was proposed. In addition, GPS-based driving path information and sensor-based real-time traffic information were also integrated to model and predict traffic flow. Following this, in the optimization layer, the DP method was used to realize the power depletion control to fully exploit the fuel-saving advantage of the battery and ensure that the SOC was not lower than the minimum value. In Yang et al. (2016), an ITS-based EMS was proposed stemming from the real-time communication connection between the vehicle and the control center. The driving conditions were classified based on the historical data. Following this, the current driving data were analyzed, and the support vector machine method was used to predict the driving conditions. In addition, energy management was realized by combining the real-time information from the control center and the GIS ramp information. In Yang et al. (2017), an ITS-based EMS was divided into online and off-line parts, and a corresponding cloud computing framework was proposed. In the off-line part, driving conditions were classified, and drivers' driving demands were predicted using the real-time data transmitted to the control center. For the online part, a well-trained support vector machine was used to recognize the driving state and select the corresponding driving behavior. The stochastic receding horizon control method was adopted to obtain optimal energy management. In Li (2016), an ITS-based EMS was proposed that was established on the cruising speed of the vehicle in front. The navigation system collected the speed in front, and the trajectory of the collected cruising speed was optimized under the premise of the safety rules. In the optimization layer, based on the optimized cruising speed and the real-time running state of the HEV, DP and MPC were used to realize energy management, which ensured cruise safety and improved the fuel economy of the HEV. In C. Sun et al. (2015b), an ITS-based predictive EMS established on real-time traffic flow data was proposed. An additional SOC planning layer was constructed based on the real-time traffic data, and the optimal SOC trajectory was solved in real time using DP. The energy management in the prediction domain was realized. Meanwhile, the update time of the SOC trajectory was similar to that of traffic flow information. In J. Hu et al. (2016), an ITS-based EMS was proposed in order to maximize the fuel economy of a HEV driving on an unsmooth road. In addition, the current and future driving information, including the dynamic speed limit and terrain information from GIS, were taken as the input for the controller. The optimization results were solved and accelerated by PMP considering the vehicle speed, the power distribution, and the engine working point. In Liu et al. (2021), an ITS-based EMS was proposed based on IoV and real-time traffic information. The speed limit curve was proposed and transformed into a spatial domain problem. According to the speed value based on driving distance, the speed planning and power distribution of HEVs were realized using DP considering the shift limit and speed fluctuation. A time adjustment factor was added to the cost function to constrain the final driving time. In He et al. (2021), physical and network systems were integrated, and an ITS-based EMS established on a cyber-physical system was proposed. The historical traffic information of a hybrid electric bus and DRL were used to conduct exploratory training for the EMS. The prior effective knowledge of the hybrid electric bus was then applied to a Toyota Prius by deep transfer learning to accelerate the convergence speed of the new EMS. In addition, V2V and V2I were combined to obtain the status parameters of surrounding vehicles and signal lights, and different operation modes were selected under different traffic conditions to realize the optimization of energy management problems.

The characteristics of different ITS-based EMSs established using real-time data are illustrated in Table 16. This type of EMS is based on real-time data, which can preset the operating rules and driving condition classification and provide the appropriate future operating state according to the real-time operating state of the vehicle in order to deal with changes in traffic information. Moreover, the behavior of the driver and the running state of the vehicle can be guided. However, this EMS has high requirements for infrastructure and relies on the real-time information interaction between the vehicle and the cloud control center. The prediction interval is also often long (e.g., 100 s). Hence, this EMS does not work well in environments with weak infrastructure or poor communication. With the continuous development and progress of technology, this strategy has a broad application prospect.

6 Conclusion and prospects

In this paper, EMSs of HEVs have been reasonably classified, and the current research results have been summarized. The rule-based EMS can obtain optimization results to a certain extent and has been widely used in practice. However, this EMS cannot achieve optimal fuel economy and fully exploit the energy-saving potential of HEVs. The global optimization-based EMS can reduce fuel consumption to the greatest extent across the entire range of driving conditions. However, it cannot be directly applied to real vehicles and is often used as a benchmark for other EMSs. In contrast, the instantaneous optimization-based EMS considers real-time performance and instantaneous fuel consumption minimization and does not require a priori knowledge of the driving cycle. Hence, it has better fuel economy and adaptability. However, this EMS is not the global optimization solution of the whole driving cycle. In addition, vehicle structural parameters, driving cycles, the determination of the cost function, and driving cycle prediction methods will affect the accuracy and effect of EMSs. Therefore, the improvement and optimization of EMSs is an effective way to balance fuel economy and real-time performance. The characteristics of the different EMSs are summarized in Table 17.

According to the current problems and the development trend of HEVs, four future research directions are proposed and are outlined in the following subsections.

6.1 EMSs based on the transient response of the HEV power system

In existing studies, the EMS is usually used as the upper controller for power distribution. Its optimization target is mainly based on the steady-state index, without taking the transient response of the components of the underlying power system into consideration. The vehicle-integrated controller needs to solve the demand and also needs to collect the vehicle running data to realize the monitoring and diagnosis of the HEV, which has high requirements for the response speed of the control system. However, during the actual driving process, transient conditions such as rapid acceleration, rapid braking, and parking account for about one-third of the driving conditions experienced. These transient response processes will be directly reflected in the power train, and the controller needs to control the bottom actuator according to the rapidly changing driving conditions. The transient response of the bottom actuator has become the key point of optimization. The transient fuel consumption and frequency response characteristics of the ICE will affect the fuel economy. In the calculation, these problems are often reduced or ignored by simplified vehicle models. Therefore, balanc-

Table 16. Summary of exemplary works on ITS-based EMSs established using static data.

Reference	Approaches	Application scenarios	Verification	Performance
Li (2016)	Cruise speed optimization DP MPC	Parallel HEV	Simulation	– Acquired the speed of the vehicle ahead and optimized the cruise speed trajectory – DP- and MPC-based power distribution – The fuel economy was improved by 4.31 %
Qian et al. (2017)	SPAT F-MPC WL-ECMS	HEV	HIL	– The optimal speed sequence was calculated by F-MPC using SPAT – Avoided stopping at red lights – Reduced the calculation time for a single step
F. Zhang et al. (2017)	V2V V2I CNN ECMS	Single-shaft parallel HEV	Simulation	– CNN-based speed trajectory prediction – Information from V2V and V2I – Adjusted the EF based on the predicted speed
Yang et al. (2017)	Cloud computing Support vector machine	Plug-in hybrid electric bus	Simulation HIL	– Driving condition clustering in off-line part – Predicted the possible driver demand – Energy management was based on the stochastic receding horizon control method
He et al. (2021)	CPS DRL V2V V2I Deep transfer learning	Hybrid electric bus Toyota Prius	Simulation	– A prior effective EMS for a hybrid electric bus was applied to a Toyota Prius by deep transfer learning – The fuel economy improved by 6.94 % and 8.12 % for DDPG and DQL, respectively.

F-MPC represents fast MPC. WL-ECMS represents the Willan-line-based ECMS. CPS represents the cyber-physical system. DDPG represents the deep deterministic policy gradients.

Table 17. The characteristics of different EMSs.

Approaches	Pros	Cons
The deterministic rule-based EMS	– Easy to implement – Small calculation cost – Good stability	– Relies on engineering experience – Less adaptability to dynamic changes – No optimal control
The fuzzy logic rule-based EMS	– Strong robustness and adaptability – Independent of model – High calculation efficiency	– Relies on engineering experience – No optimal control
The global optimization EMS	– Global optimization results – Can be used as theoretical guidance in the design of other EMSs	– Prior knowledge of driving cycle – Less adaptability – Large calculation cost
The instantaneous optimization EMS	– Real-time optimal control – Unrestricted by driving conditions – Online implementation	– No global optimization control – Relies on an accurate model
The ITS-based EMS	– Online implementation – Real-time optimal control – Broad application prospect	– Relies on infrastructure and V2X – Difficult to guarantee accuracy – Immature technology

ing and optimizing the response characteristics and real-time performance of the bottom actuator while meeting the requirements of approximate optimal control and calculation efficiency at the upper level has become a research focus.

6.2 EMS based on multi-objective optimization

Because a HEV has multiple power sources, the influence of interactions among them on performance cannot be ignored. The initial requirement for EMSs was generally the improvement of the fuel economy performance. With the continuous development of technology, scholars have also added the performance of various components of power systems into EMSs and have transformed EMSs from single-objective optimization to multi-objective optimization scenarios. At present, EMSs not only take overall fuel economy into consideration but also consider pollutant emissions, battery degradation, transient fuel consumption, and SOC retention. In addition, EMSs also need to consider the interactions between the power sources and the performance, such as fuel economy and drivability, the SOC charge–discharge characteristics, and the battery life. However, introducing the above factors into EMSs and realizing multi-objective optimization according to their interaction also needs to be paid more attention in future research.

6.3 EMS based on multi-method collaborative optimization

At present, EMSs based on a single method have their disadvantages, such as low calculation efficiency, poor adaptability, and poor real-time performance, which leads to different limitations in the optimization process and makes it difficult to fully exploit the performance potential of HEVs. For example, the fuzzy logic rule-based EMS has good real-time performance, but the optimization effect is limited. While DP can solve the global optimization solution, the driving conditions need to be known in advance, and the calculation burden is heavy. Therefore, in the process of EMS development and design, combining the advantages of various methods to achieve collaborative optimization control will be a continuous research hot spot.

6.4 EMSs based on driving condition and driver behavior prediction

Although many EMSs are established based on driving conditions, the driving conditions of HEVs are unknown during the actual driving process, which makes it impossible to obtain the optimal control results. Therefore, knowing the driving conditions in the future or for a short time is of great help with respect to improving the control performance of EMSs. At present, driving condition prediction methods based on NNs and RL are applied to EMSs, and the application of location information such as GIS and GPS also provides great help for online driving condition prediction for EMSs. In recent years, with the rapid development of the ITS and IoV technology, the vehicle can realize the planning of energy management according to the current position information and known driving condition data. In addition, regarding the subject of driving behavior, the driver will change the driving state according to subjective judgment. Different drivers may take different action in the same situation, which introduces uncertainty with respect to the driving behavior and even with respect to driving conditions. Thus, the realization of driver behavior prediction is also very helpful in predicting driving conditions. However, in the current research, the accuracy of driving condition prediction and driver behavior prediction is still difficult to guarantee, which has become a problem for future development. Therefore, future research will focus on combining the prediction process with EMSs efficiently and stably while also ensuring prediction accuracy.

Appendix A: Abbreviation

A-ECMS	Adaptive equivalent consumption minimization strategy
ANFIS	Adaptive neuro-fuzzy inference system
BPNN	Back-propagation neural network
CD	Charge depleting
CNN	Convolutional neural network
CO	Convex optimization
CS	Charge sustaining
DP	Dynamic programming
DPR	Driving pattern recognition
DRL	Deep reinforcement learning
DRNN	Deep recurrent neural network
ECMS	Equivalent consumption minimization strategy
EF	Equivalent factor
EM	Electric motor
EMS	Energy management strategy
EV	Electric vehicle
FIS	Fuzzy inference system
GA	Genetic algorithm
GIS	Geographic information system
GT	Game theory
HEV	Hybrid electric vehicle
ICE	Internal combustion engine
IoV	Internet of Vehicles
ITS	Intelligent transportation system
LFS	Load-following strategy
LSTM	Long short-term memory
MF	Membership function
MPC	Model predictive control
NMPC	Nonlinear model predictive control
NN	Neural network
NO_x	Nitrogen oxide

PFS	Power-following strategy
PMP	Pontryagin's minimum principle
PSO	Particle swarm optimization
QP	Quadratic programming
RL	Reinforcement learning
RNN	Recurrent neural network
SDP	Stochastic dynamic programming
SFS	Speed-following strategy
SMPC	Stochastic model predictive control
SPAT	Signal phase and timing
SQP	Sequential quadratic programming
TPM	Transfer probability matrices
V2I	Vehicle to infrastructure
V2V	Vehicle to vehicle

Data availability. No data sets were used in this article.

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