Recent Advancements in Connected Autonomous Vehicle Technologies 3

Yue Cao · Yuanjian Zhang · Chenghong Gu *Editors*

Automated and Electric Vehicle: Design, Informatics and Sustainability

Springer

Recent Advancements in Connected Autonomous Vehicle Technologies

Volume 3

This Springer book series shows control theory applications and the latest achievements in the field of the autonomous vehicle. It emphasizes the practical application of various control methods, with real-world experimental validations. New and developing control algorithms, including data-driven control, robust control, cooperative control, and predictive control, are discussed and applied in the connected autonomous vehicle to improve energy consumption, vehicle safety, passenger feeling, and transportation efficiency.

The book series aims to introduce essential and recent achievements in the autonomous vehicle to researchers and engineers. The individual book volumes in the series are thematic. The goal of each volume is to give readers a comprehensive overview of how developing control algorithms can be used to improve vehicle performance and transportation efficiency. As a collection, the series provides valuable resources to a broad audience in academia, the engineering research community, industry, and anyone else who are looking to expand their knowledge of the autonomous vehicle.

Yue Cao · Yuanjian Zhang · Chenghong Gu
Editors

Automated and Electric Vehicle: Design, Informatics and Sustainability

Springer

Editors
Yue Cao
School of Cyber Science and Engineering
Wuhan University
Wuhan, Hubei, China

Suzhou Research Institute of Wuhan University
Suzhou, China

Yuanjian Zhang
Department of Aeronautical and Automotive Engineering
Loughborough University
Loughborough, Leicestershire, UK

Chenghong Gu
Department of Electronic and Electrical Engineering
University of Bath
Bath, UK

This work was supported by Suzhou Municipal Key Industrial Technology Innovation Program (SYG202123).

ISSN 2731-0027 ISSN 2731-0035 (electronic)
Recent Advancements in Connected Autonomous Vehicle Technologies
ISBN 978-981-19-5750-5 ISBN 978-981-19-5751-2 (eBook)
https://doi.org/10.1007/978-981-19-5751-2

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Contents

Chapter 1
Energy Efficient Control of Vehicles

Yuanjian Zhang and Zhuoran Hou

Abstract Electric vehicles (EVs) have the advantages of energy saving and environmental protection, which are favoured by major vehicle companies nowadays. However, the problem of how to effectively improve the economy has been a hot spot and difficult research point of the vehicle control strategy. Therefore, this chapter introduced the mainstream algorithms currently used as energy management strategies, and analysed the advantages of each method. This chapter begins with an introduction to energy integrated control for electric vehicles. Since the control scheme is related to architecture, this chapter then introduces the common architectures of EVs. Finally, the rule-based energy management strategy and the optimization-based energy management strategy are highlighted, and the vehicle architectures to which the different strategies are adapted are analyzed. Finally, the development and characteristics of the strategies are summarized.

Keywords Electric vehicle · Energy management strategy · Energy consumption · Rule-based · Optimization-based

List of Abbreviations

EVs	Electric Vehicles	PHEV	Plug-in Hybrid Electric Vehicle
SOC	State of Charge	DMC	Dynamic Matrix Control
DP	Dynamic Programming	MPHC	Model Predictive Heuristic Control
PMP	Pontriagin Minimum Principle	MPC	Model Predictive Control

Y. Zhang (✉)
Department of Aeronautical and Automotive Engineering, Loughborough University, Leicestershire, UK
e-mail: y.y.zhang@lboro.ac.uk

Z. Hou
State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun, China

Y. Cao et al. (eds.), *Automated and Electric Vehicle: Design, Informatics and Sustainability*, Recent Advancements in Connected Autonomous Vehicle Technologies 3, https://doi.org/10.1007/978-981-19-5751-2_1

ECMS	Equivalent Consumption Minimization Strategy	LQR	Linear Quadratic Regulator
HEV	Hybrid Electric Vehicle		

1.1 Introduction

As one of the main travel tools, the technology in the automotive field is also developing rapidly. In the automotive field, energy management is mainly used as a multi-energy source distribution management technology, which has been widely studied and applied [1]. The traditional internal combustion engine vehicle takes advantage of the high energy density of petroleum fuel to power the vehicle for long distances. However, the internal combustion engine has the disadvantages of exhaust pollution and low fuel economy. The main reasons for the fuel economy shortage of internal combustion engine are as follows.

(1) Internal combustion engine works in a lower efficiency area under some working conditions;
(2) Loss of vehicle energy during braking.

With the development of vehicles, people further improve the working efficiency of the engine through other power sources (such as batteries to provide electric energy, motor to provide power output). Batteries and motors are added to the traditional internal combustion engine to optimize the working area of the engine, and then improve the economy. The energy distribution between motor and internal combustion engine becomes the focus and difficulty of the research. In recent years, fuel oil, natural gas and fuel cell are used as the power source to drive the automobile. Energy management technology becomes the key technology to improve the rational distribution of power source energy. The reasonable distribution of electric power (electric energy management) is the key factor to improve the economy of electric vehicles. This chapter mainly analyzes and explores energy management of multi-power source vehicles for the purpose of improving automobile economy.

1.2 Architecture

In petrol-electric hybrid vehicles, the engine and motor are the main power components to drive the vehicle, and the rational distribution of engine and motor power has become the core technology of energy management [2]. The rationality of energy distribution is beneficial to realize the decoupling of engine speed and torque, improve the working area of the engine and improve the working efficiency of the engine. At present, petrol-electric hybrid electric vehicles are mainly divided into series, parallel and hybrid. The series hybrid electric vehicle drives the generator to generate electricity and provides energy output power to the motor. This structure can achieve the decoupling of engine speed and torque. However, this structure is electrically coupled and has a large energy loss due to the energy conversion process, as shown in Fig. 1.1.

Parallel hybrid vehicle also has motor and engine two power components. They are mechanically coupled and reduce the loss of energy conversion. However, the simultaneous decoupling characteristics of engine speed and torque are limited. According to the different structure, it can also achieve the decoupling characteristics of speed as shown in Fig. 1.2. The purpose of optimizing engine performance and improving automobile economy is realized.

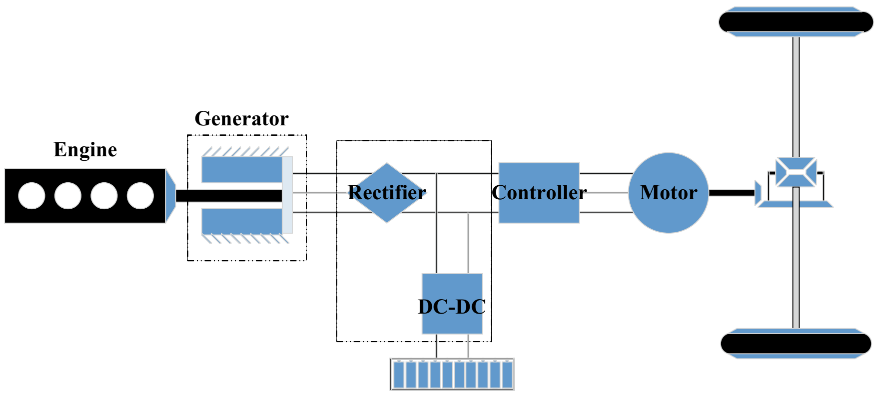

Fig. 1.1 The architecture of the series hybrid electric vehicle

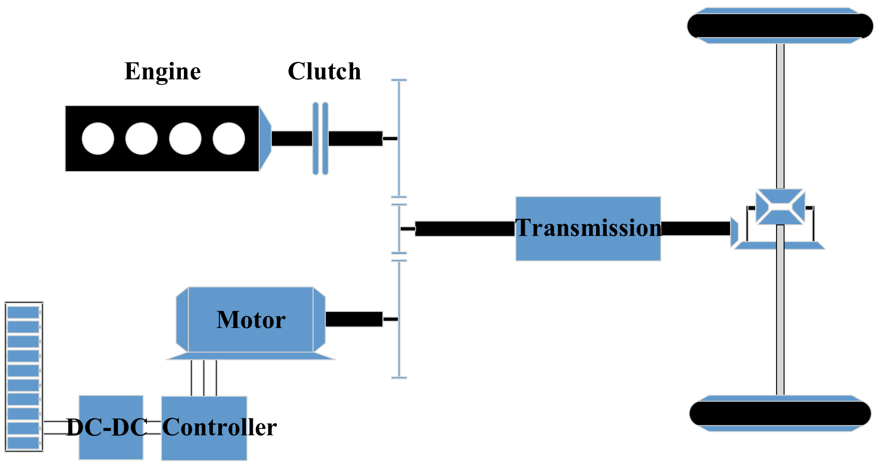

Fig. 1.2 The architecture of the parallel hybrid electric vehicle

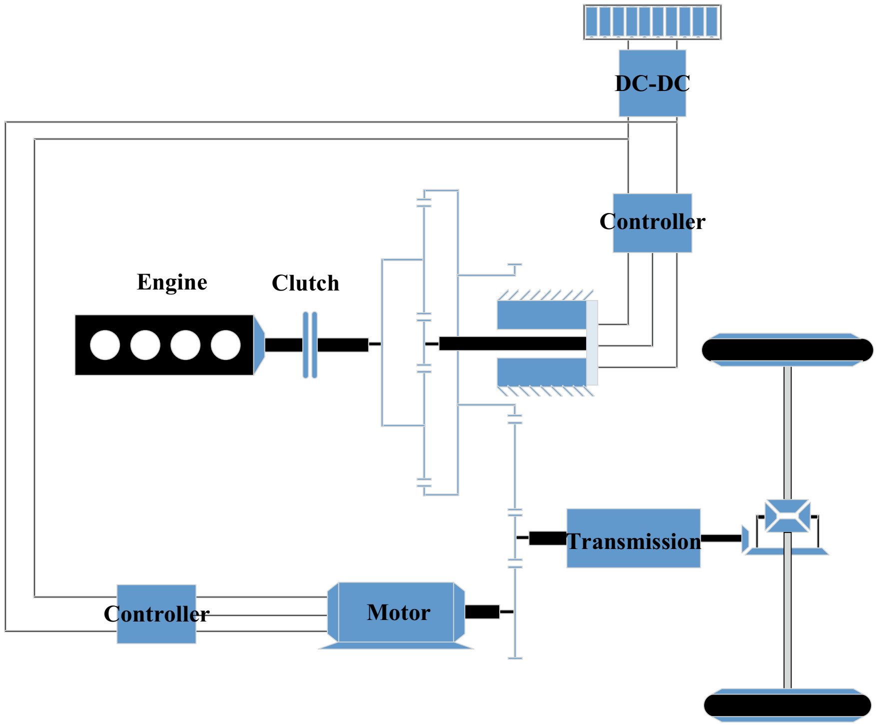

Fig. 1.3 The architecture of the hybrid hybrid electric vehicle

Hybrid hybrid electric vehicle has more than two power components, combining the advantages of series and parallel. The architecture of it is shown in Fig. 1.3. The energy distribution of the power shunt type is realized by using the planetary array structure, and the working efficiency of the engine is improved. Series and parallel uses clutch to realize the switch between series and parallel, which improves the economy. However, the structure of hybrid hybrid electric vehicle is complex and the control logic is complex, so the energy distribution and output between different power components become the key and difficult point.

1.3 Rule-Based Energy Management Strategy

At present, energy management is mainly divided into two research methods: energy management control strategy based on rules and energy management control strategy based on optimization [3]. Rule-based energy management strategy mainly includes deterministic rules and fuzzy rules. It makes corresponding control strategy through a large number of experiments, experts' experience, mathematical model and other known conditions. It is simple and easy to implement, good reliability and other advantages, and is widely used [4, 5].

1.3.1 Energy Management Control Based on Deterministic Rules

1.3.1.1 Thermostat Control

Thermostat control strategy refers to the engine at a constant power output. Thermostat control strategy is most used in series petrol-electric hybrid vehicle energy management [6]. The engine of series vehicles can be decoupled (electrically coupled) from the speed and torque of the vehicle's output shaft. The engine works at the optimal working point and drive the generator to generate electricity with constant power output. Battery state of charge (SOC) is the only threshold for engine startup, as shown in Fig. 1.4.

When the battery SOC drops to a set threshold, the engine starts and outputs constant power near the optimal fuel consumption point (single point control), as shown in Table 1.1. If the output power of the engine driven generator is higher than the power required by the motor to drive the car, part of the power is used for the motor to drive the car, and the other part of the power controller controls the generator to charge the battery pack.

where is the request power; is the engine power; . P_{Best}. is the most economical operating power at current engine speed; P_b is the battery power.

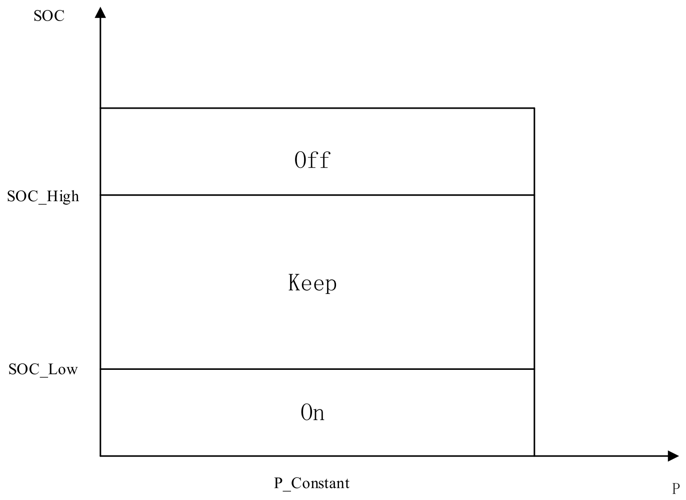

Fig. 1.4 Thermostat control

Table 1.1 Thermostat control. $SOC < SOC_{Low}$

. $P_r > 0$.	.. $P_r \leq 0$ ..
$P_e = P_{Best}$ $P_b = P_r - P_{Best}$	$P_e = 0$ $\lvert P_b \rvert = \lvert P_r \rvert - \lvert P_{Brake} \rvert$

Table 1.2 Thermostat control. $SOC > SOC_{High}$

$P_r > 0$	$P_r \leq 0$
$P_e = 0$ $P_b = P_r$	$P_e = P_b = 0$ $P_{Brake} = P_r$

Table 1.3 Thermostat control. $SOC_{Low} < SOC < SOC_{High}$

$P_r > 0$		$P_r \leq 0$
$P_e = P_{Best}$ $P_b = P_r - P_{Best}$	$P_e = 0$ $P_b = P_r$	$P_e = 0$ $\lvert P_b \rvert = \lvert P_r \rvert - \lvert P_{Brake} \rvert$

When the SOC rises to the set high threshold, the engine shuts off and the battery provides all the instantaneous power requirements of the vehicle, as shown in Table 1.2. The battery provides extra power to the motor when the power generated by the engine's generator is less than what the motor needs to drive the car.

When the SOC is between the two thresholds, power components remain in the previous operating state, as shown in Table 1.3.

In thermostat control, the battery balances the power output from the engine with the power required by the motor. The control system of thermostat control strategy is simple and easy to implement. However, there are more energy conversion times and the efficiency is not high. Excessive circulation of the battery will have an adverse effect on the battery itself.

1.3.1.2 State Machine Control

Finite state machine control, referred to as state machine control, is a mathematical model consisting of multiple states. The State represents a certain property of an object [7]. By triggering the set conditions, the transition between different states can be realized. The transfer between states is realized by the logic conditions of thresholds triggered by real-time signals. The action after entering each state is to execute the corresponding control strategy. Since any two states can be transferred, only part of the transition relationship between states is established.

In the automotive field, according to different optimization purposes, through a large number of experiments and experts' experience, the vehicle is divided into different operating states. Different control thresholds are used to transfer the states between each operating state. For example, most fuel cell vehicles use state machine control to coordinate the energy distribution between different power sources and improve the economy of the vehicle. The control strategy is simple and easy to implement and widely used.

1.3.1.3 Power Following Strategy Control

The power following control strategy determines the working state of the engine according to the SOC of the battery and the load of the vehicle, which is mostly used in the series structure of petrol-electric hybrid electric vehicle. It is an optimization of the thermostat control strategy. Different working points of the engine can be determined according to the different running states of the vehicle. The power of the engine follows the power required by the car to drive. Similar to the traditional vehicle, the engine speed and torque in the series hybrid electric vehicle are decoupled from the vehicle output shaft. Compared with traditional cars, the engine speed is not directly determined by the speed, and the engine can work under the economic speed. Compared with the thermostat control strategy, the engine with power following control strategy generally operates near the optimal economic operating curve. Therefore, the power following control strategy is more adaptable to external power changes, the output power is more reasonable, reduces the number of charging and discharging cycles of the battery, and is more conducive to the protection of the battery [8]. But the output power of the engine should always follow the demand power of the vehicle, the power varies widely, and the working area of the engine becomes larger. Therefore, it is difficult to ensure that the engine works in higher fuel economy areas.

In the structure of serial-type hybrid electric vehicle, the motor is used as a direct power component for power output. The energy source of the motor (power source) is obtained by the power from the battery and the power from the generator driven by the engine. Energy management mainly distributes engine power and battery power for economic energy consumption. The power following strategy controls the start/stop working mode of the engine according to the SOC of the battery and the power of the vehicle, as shown in Fig. 1.5.

When the SOC of the battery is in low power or the power required by the vehicle is large, the engine starts to work. The engine stops working when the SOC of the battery is in a high power state and the vehicle needs a large power. In the case of other SOC and vehicle power requirements, the engine keeps the working state of the previous moment unchanged. If the output power of the engine driven generator cannot meet the demand power of the vehicle, the engine can output the maximum power under the condition of ensuring relatively economic efficiency, and the insufficient power is provided by the battery. If the required power of the vehicle is less than the minimum economic power of the engine, the engine outputs the minimum economic power, and the excess power charges the battery pack. Under different SOC and power requirements, the distribution schemes of engine power and motor power are shown in Tables 1.4, 1.5 and 1.6.

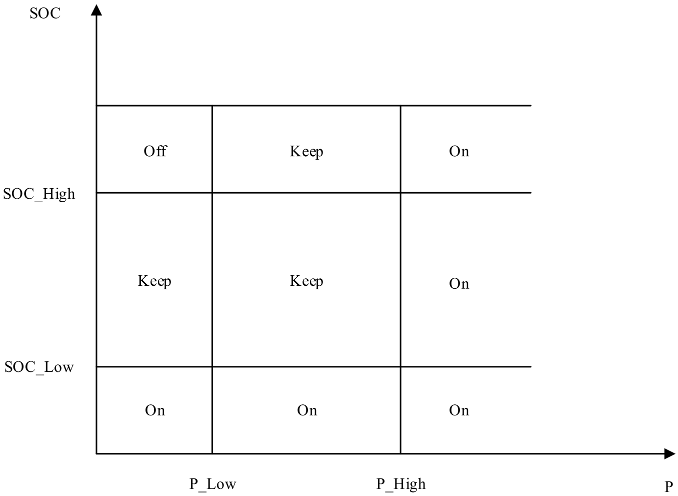

Fig. 1.5 Power following strategy control

Table 1.4 Power following strategy control. $SOC < SOC_{Low}$

P_r	P_e	P_b
$0 < P_r < P_{Low}$	$P_e = P_{Low}$	$P_b = P_e - P_r$
$P_{Low} \le P_r \le P_{High}$	$P_e = P_r$	$P_b = 0$
$P_{High} < P_r$	$P_e = P_r$	$P_b = 0$
$P_r \le 0$	$P_e = 0$	$\lvert P_b \rvert = \lvert P_r \rvert - \lvert P_{Brake} \rvert$

Table 1.5 Power following strategy control. $SOC_{Low} \le SOC \le SOC_{High}$

P_r	P_e	P_b
$0 < P_r < P_{Low}$	$P_e = P_{Low}$	$P_b = P_e - P_r$
	$P_e = 0$	$P_b = P_r$
$P_{Low} \le P_r \le P_{High}$	$P_e = P_r$	$P_b = 0$
	$P_e = 0$	$P_b = P_r$
$P_{High} < P_r$	$P_e = P_{High}$	$P_b = P_r - P_e$
$P_r \le 0$	$P_e = 0$	$\lvert P_b \rvert = \lvert P_r \rvert - \lvert P_{Brake} \rvert$

Table 1.6 Power following strategy control. $SOC_{Low} \le SOC \le SOC_{High}$

P_r	P_e	P_b
$0 < P_r < P_{Low}$	$P_e = 0$	$P_b = P_r$
$P_{Low} \le P_r \le P_{High}$	$P_e = P_r$	$P_b = 0$
	$P_e = 0$	$P_b = P_r$
$P_{High} < P_r$	$P_e = P_{High}$	$P_b = P_r - P_e$
$P_r \le 0$	$P_e = 0$	$P_b = 0$

1.3.2 *Energy Management Control Based on Fuzzy Rules*

1.3.2.1 Traditional Fuzzy Logic Control

Fuzzy logic control is a kind of control method based on fuzzy set theory, fuzzy language variables and fuzzy reasoning [9]. Different from the control strategy based on the deterministic rules, fuzzy logic control strategy does not need to know the specific mathematical model of the controlled object, but relies on experience to skillfully control a complex process. When the experience is summed up in words, a qualitative and imprecise rule of control is generated. Then it is quantified into fuzzy control algorithm by fuzzy mathematics. For example, peak power SOC and vehicle power demand are described as high, medium and low. The value of the output is obtained by definite rules and fuzziness as shown in Fig. 1.6.

1.3.2.2 Adaptive Fuzzy Logic Control

Adaptive fuzzy logic control is a fuzzy logic system with adaptive learning algorithm added to the traditional fuzzy logic control technology. Its learning algorithm relies on data information to adjust the parameters of the fuzzy logic system. For example, in a certain driving cycle, the energy management effect is not very ideal, then the learning algorithm will adjust the control rules to adapt to the driving cycle. An adaptive fuzzy controller can be composed of a single adaptive fuzzy system or several adaptive fuzzy systems. Adaptive fuzzy control has two different forms:

(1) Direct adaptive fuzzy control: according to the actual performance of the system and the deviation between ideal performance, through a certain method to adjust the parameters of the controller directly;

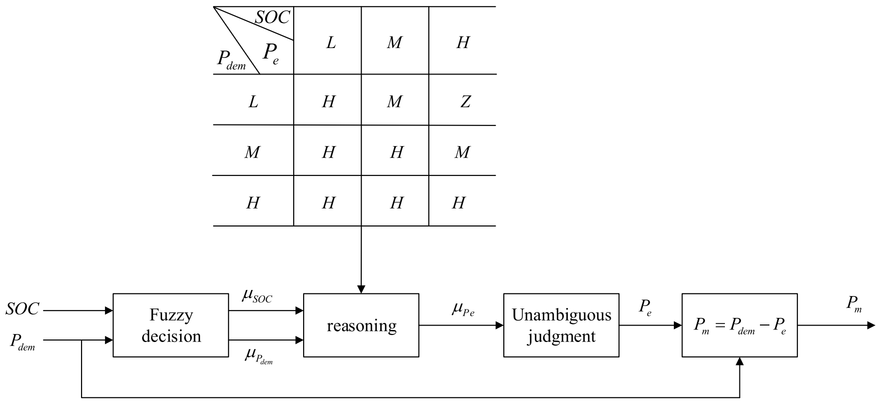

Fig. 1.6 Traditional fuzzy logic control

(2) Indirect adaptive fuzzy control: the model of the control object is obtained by on-line identification, and the fuzzy controller is designed according to the model.

1.3.2.3 Predictive Fuzzy Logic Control

Predictive fuzzy logic control strategy is organically combined with fuzzy logic control and predictive control, which can better adapt to the needs of complex process control. Its algorithm basically revolves around two directions [7].

(1) Taking process prediction information as the core, fuzzy identification and modeling methods are introduced into conventional predictive control. That is, fuzzy technology is introduced into the information processing link of the prediction model, so as to constitute the predictive fuzzy logic control. It includes using fuzzy modeling method to build object prediction model and using fuzzy technology to compensate prediction error and control law. The former uses the fuzzy model as the prediction model to improve the accuracy of predicting the output of complex objects, which is beneficial to improve the stability and robustness of the prediction algorithm. The latter uses fuzzy reasoning to compensate the output deviation of the model. And the advantage of fuzzy reasoning in uncertain information processing is used to make up the deficiency of traditional predictive control algorithm in system information processing.
(2) Taking fuzzy decision optimization as the core, the membership function and control rules of traditional fuzzy controller are optimized by using the correlation principle of predictive control and self-calibration principle, so that a certain performance measurement index tends to be optimal. Because the core of predictive control is rolling optimization, the whole algorithm can be reduced to a performance optimization problem. The traditional predictive control adopts the optimization method based on linear quadratic objective function, which minimizes the objective function in the control time domain to obtain the optimal control law. However, for complex systems, the cost of this method is very large, sometimes even impossible to achieve. To some extent, fuzzy logic control is to choose a set of controller parameters to make the controller output close to the optimal control law. Therefore, fuzzy decision can be introduced into predictive control algorithm, and various predictive fuzzy control algorithms based on fuzzy decision optimization can be obtained.

1.4 Optimization-Based Energy Management Strategy

Optimization-based energy management strategy is divided into global-optimization-based energy management strategy and instantaneous-optimization-based energy management strategy [10]. The control strategy based on optimization takes into account all kinds of operating conditions and needs to consider the transient and fuel economy in the whole driving cycle. Compared with the rule-based control strategy, it has better economic effect, but the calculation is large, which increases the control difficulty.

1.4.1 Global-Optimization-Based Energy Management Strategy

1.4.1.1 Dynamic Programming

The basic idea of the dynamic programming (DP) algorithm is to transform a large multi-stage problem into multiple sub-problems of the same type. By solving the optimal solution of the sub-problem, the recursive optimization of the original problem is completed. The algorithm is based on the Bellman's principle of optimality. As a multi-stage global-optimization-based energy management strategy, regardless of its past states and decisions, the remaining decisions must constitute an optimal sub-strategy. In short, any part of the sub-strategies in the optimal policy must also be optimal [11].

The algorithm is widely used for non-aftereffect problems with deterministic conditions, where decisions are made according to stages. The term " non-aftereffect " means that when the state of the system at a certain stage is known, then the change of the system state after that stage is only related to the current stage and not to all previous stages. Therefore, the solution process of the algorithm starts from the termination stage. The algorithm is solved recursively within the boundary conditions by finding the optimal sub-problem for each stage. For each stage of the sub-problem, the optimal solution of the previous sub-problem is used in the solution process. Thereby, the complexity of the algorithm is reduced and the speed of the algorithm solution is accelerated. For DP algorithms, the following aspects need to be clarified first.

(1) Determine the stage of the optimization problem. Decompose a global optimization problem into several stages of sub-problems to be solved. The amount of stages in the solution process is denoted as k.
(2) Determine state variables and control variables for the optimization problem. The state of the system at each stage is described by the state variables. The state variable at stage k is denoted as x_k. The decision that acts on the control system to change the system state is described by the control variable. The control variables when the system state is x_k are denoted as $u_k(x_k)$. In the global optimization problem with k stages, there are $k+1$ state variables and k control variables.
(3) Determine the constraints of the optimization problem. The state variables and control variables of the system often have various constraints, including linear and nonlinear constraints, equation constraints and inequality constraints.

Therefore, in the algorithm solution process, the state and control variables must satisfy the constraints of the optimization problem. The optimal control sequence under the global is solved within the allowed range to complete the optimal control of the system.

(4) Determine the state transfer equation of the optimization problem. The state transfer equation describes the law of the system changing from the state of the current stage to the state of the next stage. By determining the state variables and control variables of the current stage, the state variables of the next stage can be obtained to realize the transfer of the system state.
(5) Determine the cost function of the optimization problem. The cost function is used to measure the impact of the control system on the system performance in a certain state. The function depends on the current state variables and control variables. At the kth stage, when the system state variable is x_k and the control variable is u_k, the cost function is denoted as $J(x_k, u_k)$.

1.4.1.2 Pontryagin Minimum Principle

Pontriagin minimum principle (PMP), also known as maximum principle, is a method to solve optimal control problems under the condition that control vector is limited [12]. That is, under finite state or input conditions, an optimal control variable is solved to transfer the system from one state to another. The mathematical description of PMP is as shown in (1.1).

$$H(x(t), u^*(t), \lambda(t), t) \leq H(x(t), u, \lambda(t), t), \forall u \in U, t \in [t_0, t_f] \tag{1.1}$$

where U is the control domain; $u^*(t)$ is the optimal control variable; $x(t)$ is the system state variable; $\lambda(t)$ is the coordination state variable.

The mathematical description of a minimum is as shown in (1.2).

$$J = \phi(x(t_f), t_f) + \int_{t_0}^{t_f} L(x(t), u(t), t)dt \tag{1.2}$$

where $L(x(t), u(t), t)$ is the instantaneous cost value related to the control variable; $\phi(x(t_f), t_f)$ represents terminal constraint.

Because the control variable has constraints, the objective function cannot be equal to 0 by taking the derivative of the objective function with respect to the control variable. To solve the minimum problem, the constraint equation is transformed into a non-constraint equation for solution by using Lagrange multiplier method. And then the Hamiltonian function in PMP is obtained. The formula is as shown in (1.3).

$$H(x(t), u(t), \lambda(t), t) = \lambda(t)f(x(t), u(t), t) + L(x(t), u(t), t) \tag{1.3}$$

The PMP optimization algorithm aims to find the optimal solution through calculation, so that the Hamiltonian function can obtain a minimum value in a finite set. The formula is as shown in (1.4).

$$u^*(t) = argminH(x(t), u(t), \lambda(t), t) \tag{1.4}$$

When obtaining the optimal control quantity u of the density function, the following conditions must be met (1.5)–(1.8).

$$\dot{\lambda}(\mathrm{t}) = -\frac{\partial H(x(t), u(t), \lambda(t), t)}{\partial x} \tag{1.5}$$

$$\dot{x}(t) = \frac{\partial H(x(t), u(t), \lambda(t), t)}{\partial \lambda} \tag{1.6}$$

$$\mathbf{x}^*(t_0) = x_0 \tag{1.7}$$

$$\mathbf{x}^*(t_f) = x_{t \arg et} \tag{1.8}$$

The necessary conditions given by PMP can be used to search for optimal control alternatives, which is called extreme control. The PMP guarantees optimal control. If it exists, it must be extreme control. If the optimal control problem has only one solution, and only one extreme control quantity, then this is the optimal control solution. Even if several extremum controls are found, it is relatively easy to apply them all at once. The optimal control is then identified as the extremum that gives the lowest total cost.

In the optimal energy management problem of gasoline-electric hybrid vehicles, the state quantity is usually SOC, and the control quantity is the output power of the engine or the output power of the motor. The state SOC must be between $SOC_{\max}$ and $SOC_{\min}$. Thus, the set of admissible states is $\Omega_{SOC}(t) = [SOC_{\min}, SOC_{\max}]$. A control quantity $P_{batt}(t)$ exists in a set of permitted control $U_{P_{batt}}(t) = \left[P_{batt,\min}(t), P_{batt,\max}(t)\right]$. The objective function is usually fuel consumption, while engine exhaust emissions, battery aging, drivability, thermal dynamics and other factors can be included. The formula is shown in (1.9).

$$J = \varphi(\mathbf{x}(t_f)) + \int_{t_0}^{t_f} L(\mathbf{x}(t), \mathbf{u}(t), t)dt \tag{1.9}$$

The Hamiltonian function of energy management problems of gasoline-electric hybrid vehicles is shown in (1.10).

$$
\begin{aligned}
& H\big(SOC(t), P_{batt}(t), \lambda(t), P_{req}(t)\big) \\
& \quad = \overset{\bullet}{m}_f\big(P_{batt}(t), P_{req}(t)\big) + (\lambda(t) + w(SOC)) \cdot \overset{\bullet}{SOC}(t)
\end{aligned} \tag{1.10}
$$

The necessary conditions for the objective function to obtain the optimal control solution are shown in (1.11)–(1.16).

$$
P^*_{batt}(t) = \arg \min_{P_{batt}(t) \in U_{P_{batt}}} H\big(P_{batt}(t), SOC(t), \lambda(t), P_{req}(t)\big) \tag{1.11}
$$

$$
\overset{\bullet}{SOC}{}^*(t) = f\big(SOC^*(t), P^*_{batt}(t)\big) \tag{1.12}
$$

$$
\overset{\bullet}{\lambda}{}^*(t) = -\big(\lambda^*(t) + w(SOC)\big)\frac{\partial f}{\partial SOC}(SOC^*, P^*_{batt}) = h(SOC^*(t), P^*_{batt}(t), \lambda^*(t)) \tag{1.13}
$$

$$
SOC^*(t_0) = SOC_0 \tag{1.14}
$$

$$
SOC^*(t_f) = SOC_{t\arg et} \tag{1.15}
$$

$$
SOC_{\min} \le SOC^*(t) \le SOC_{\max} \tag{1.16}
$$

(1.12) and (1.13) represent two first-order differential equations of the variables SOC and λ. Although the two-point boundary value problem is completely defined, because one of the boundary conditions is defined at the final time, it can only be solved numerically using an iterative program.

1.4.2 Instantaneous-Optimization-Based Energy Management Strategy

1.4.2.1 Equivalent Consumption Minimum Strategy

The equivalent consumption minimization strategy (ECMS) was first proposed by Paganelli (1999) [13]. ECMS is an energy management strategy of instantaneous optimization. Its essence is to equivalent the battery power consumption to fuel consumption, that is, the fuel consumption of the vehicle into the equivalent fuel consumption of the engine and motor. ECMS and PMP algorithms are very similar, and their objective functions, too. When the ECMS was initially applied to a gasoline-electric hybrid vehicle vehicle (HEV), the difference between the initial and final charged state of the battery was very small. Negligible relative to the total amount of energy used. This means that the power storage system serves only as an energy buffer. Eventually all the energy comes from fuel. And the battery can be thought of as an auxiliary reversible fuel tank. Any stored electrical energy used during the battery discharge phase must be replenished later using fuel from the engine or through regenerative braking. With the development of plug-in hybrid electric vehicle (PHEV) vehicles, ECMS technology is also gradually applied to PHEV.

The principle of ECMS is to take the power battery as a virtual engine and convert the electric energy consumed into the fuel. The equivalent fuel consumption factor determines the fuel-electric conversion efficiency of the vehicle power system and plays a controlling role in the fuel economy of the vehicle, as shown in (1.17).

$$\dot{m}_{eqv}(x(t), u(t), t) = \dot{m}_f(u(t), t) + \lambda \cdot \dot{m}_m(x(t), u(t), t) \tag{1.17}$$

where $\dot{m}_{eqv}(x(t), u(t), t)$ is the instantaneous equivalent fuel consumption; $\dot{m}_f(u(t), t)$ is the instantaneous fuel consumption of the engine; $\dot{m}_m(x(t), u(t), t)$ is the instantaneous electric consumption of the motor equivalent to the fuel consumption; λ is the equivalent factor.

In driving cycles, the fuel consumption of the vehicle should be minimized to improve the fuel economy of the vehicle. Thus, the objective function expression of ECMS optimized energy control is established as shown in (1.18).

$$J(t) = \min \int_0^t \dot{m}_{eqv}(t)dt = \min \int_0^t (\dot{m}_f + \lambda \cdot \dot{m}_m)dt \tag{1.18}$$

The Hamiltonian function is established as shown in (1.19).

$$\mathrm{H(x(t),u(t), \lambda(t),t)} = \dot{m}_f(u(t), t) + \lambda \cdot f(x(t), u(t), t) \tag{1.19}$$

where $u(t)$ is the request torque of the motor; $x(t)$ is SOC of power battery; $f(x(t), u(t), t)$ is the instantaneous change value of SOC.

To find the optimal solution through calculation, so that the Hamiltonian function can obtain a minimum value in a finite set, as shown in (1.20).

$$u^*(t) = \arg\min H(x(t), u(t), \lambda(t), t) \tag{1.20}$$

where $u^*(t)$ is the optimal solution. Synergistic state variables and state transition variables should meet (1.21)–(1.26).

$$\dot{\lambda}(t) = -\frac{\partial H}{\partial x} = -\frac{\partial}{\partial x}\dot{m}_f(u(t), t) - \lambda(t)\frac{\partial}{\partial x}f(x(t), u(t), t) \tag{1.21}$$

$$\dot{x}(t) = \frac{\partial H}{\partial \lambda} = f(x(t), u(t), t) \tag{1.22}$$

$$SOC \in [SOC_{\min}, SOC_{\max}] \tag{1.23}$$

$$P_{batt} \in [P_{batt\_\min}, P_{batt\_\max}] \tag{1.24}$$

$$T_m \in [T_{m\min}, T_{m\max}] \tag{1.25}$$

$$T_e \in [T_{e\min}, T_{e\max}] \tag{1.26}$$

When the demand torque of the vehicle is known, the optimal output torque sequence of the motor is calculated according to the relationship between the engine, motor and the total demand torque. The optimal output torque of the engine is obtained as shown in (1.27).

$$T_e^*(t) = T_{req}(t) - T_m^*(t) \tag{1.27}$$

where $T_{req}(t)$ is the torque of the instantaneous demand of the vehicle; $T_e^*(t)$ is the optimal allocation torque of the engine; $T_m^*(t)$ is the optimal allocation torque of the motor.

1.4.2.2 Model Predictive Control

In the late 1970s, the emergence of dynamic matrix control (DMC) and model predictive heuristic control (MPHC) marked the birth of model predictive control (MPC) [14]. MPC has been a great success in the process industry since its early development and attracted many scientists to apply it to other fields. With the deepening of research and application of MPC, some scholars gradually applied MPC to vehicle control field. MPC algorithm has three main components: prediction model, rolling optimization and feedback correction. These three parts are also important differences between MPC control algorithm and other controls.

(1) Prediction model

As MPC is a predictive control algorithm based on predictive model, model plays a particularly important role in MPC. However, due to the particularity of predictive control algorithm, the requirements on the model are different from other control algorithms. Predictive control emphasizes the function of the model rather than the structure of the model. Therefore, the range of prediction models available is very wide. As long as the model has the power to predict the future input and output information of the system according to the past input and output information of the system, it can be used as a prediction model. Equation of state and transfer function can realize the above functions and can be used as prediction models naturally. Nonparametric models are common in practical industrial processes, such as step response model and impulse response model. In addition, distributed parametric system and nonlinear system models can also be used as prediction models as long as they meet the requirements of prediction models. Because of the diversity of prediction model forms, the model structure forms in traditional control are greatly expanded, and it is more convenient and fast to build models based on information in practical engineering applications.

(2) Rolling optimization

In predictive control, the output control sequence is determined by the optimization of the objective function. In other words, MPC is also an optimal control algorithm. Because the determination of performance indicators is to achieve the expected control objectives, the selection of performance indicators according to the actual situation needs to be emphasized. If the accuracy of control results is highly required, the minimum variance between system output and expected output can be selected as the performance indicator. If the demand for control energy is higher, the control focus can be placed on the control energy when the output varies within a certain range. But the optimization of performance index in predictive control is obviously different from the traditional optimal control. Because the traditional optimal control is based on a fixed optimization index of the whole bureau. The optimization index in predictive control is not invariable. Its manifestation is closely related to the present moment, which is a rolling finite time domain performance index. In other words, at each sampling moment, the performance indicator only covers a period of time from that moment to a certain future. Therefore, the optimization range at each sampling point is different. This kind of rolling optimization in finite time domain obviously can only obtain global suboptimal solution. However, due to its characteristics of repeated online optimization, it is convenient to deal with the uncertainty caused by model mismatch, interference and time variation. It actually ends up keeping the control optimal.

When the system model is in the form of state space as shown in (1.28) and (1.29).

$$x_{k+1} = Ax_k + Bu_k \tag{1.28}$$

$$y_{k+1} = Cx_k \tag{1.29}$$

The objective function is shown in (1.30).

$$J = \sum_{j=0}^{N} \{\|y(k+j|k)\|_{R_{zz}} + \|u(y(k+j|k))\|_{R_{uu}}\} + F(x(k+N|k)) \tag{1.30}$$

where N is the length of time of optimization calculation in rolling optimization; $F(x(k+N|k))$ is terminal cost function; $\|u(y(k+j|k))\|_{R_{uu}}$ is the weighted norm of the input term; $\|y(k+j|k)\|_{R_{zz}}$ is the weighted norm of the output item, and the specific expression is shown in (1.31).

$$\|y(k+j|k)\|_{R_{zz}} = y(k+j|k)^T R_{zz} y(k+j|k) \tag{1.31}$$

According to the prediction model, MPC controller predicts the future output information of the system within N step length after time k. Then the control sequence with length N is calculated by objective function optimization. Then the P step-long control sequence is applied to the system. The above problem is simplified to a traditional Linear quadratic regulator (LQR) problem. Therefore, the problem can be expressed as shown in (1.32)–(1.36).

$$\min_u J = \sum_{j=0}^{N} \{\|y(k+j|k)\|_{R_{zz}} + \|u(y(k+j|k))\|_{R_{uu}}\} \tag{1.32}$$

$$x(k+j+1|k) = Ax(k+j|k) + Bu(k+j|k) \tag{1.33}$$

$$x(k|k) \equiv x(k) \tag{1.34}$$

$$y(k+j|k) = Cx(k+j|k) \tag{1.35}$$

$$|u(k+j|k)| \leq u_m \tag{1.36}$$

Then convert the above problems into common standard optimization problems, as shown in (1.37).

$$y(k+N|k) = CA^N x(k|k) + CA^{N-1}Bu(k|k) + CBu(k+1|k) \tag{1.37}$$

By combining, extending, and distorting the above equations, the matrix form as shown below can be derived by (1.38).

$$\min_{U(k)} J = \min_{U(k)} [H_2^T U(k) + \frac{1}{2} U(k)^T H_3 U(k)] \tag{1.38}$$

And satisfy the constraint conditions as shown in (1.39).

$$\begin{bmatrix} I_N \\ -I_N \end{bmatrix} U(k) \leq u_m \tag{1.39}$$

At k sampling, a control sequence of length H_p is obtained by optimizing computation based on the current state of the system and the prediction model. Then the control sequence is applied to the system in the control interval of length H_p. Usually $H_p = 1$, that is, only the first control in the control sequence is used. At $k+1$, repeat the above steps. With the advance of sampling time, the rolling optimization and control are realized.

(3) Feedback correction

In order to improve the control effect, the baseline of MPC rolling optimization at each sampling point should be consistent with the actual situation. However, due to the complexity and changeability of the actual system, it is impractical to establish an accurate mathematical model of the system. And from the practical point of view, there is no need to build an extremely accurate model. On the contrary, in practice it is easy to obtain a rough model of the system to describe its dynamic characteristics. Since when a fixed prediction model is used to describe the system, many factors existing in the actual system, such as interference, time variation, nonlinearity and model mismatch, will lead to such a fixed model deviating from the real situation of the system. So it is necessary to use additional means to correct for differences. According to the knowledge of traditional control theory, feedback can effectively overcome the influence of interference and obtain closed-loop stability. MPC rolling optimization works best when it is based on feedback. MPC obtains the control sequence of given length by optimizing the objective function at the current sampling point. Then the first term of the control sequence is applied to the system as the actual control quantity. At the next sampling time, the output information of the system is first used for feedback. Correct or compensate the prediction model. Then a new round of optimization begins. This ensures that each optimization and control is based on the latest state of the system and helps to reduce the distortion of optimization datum due to interference. The important role of output information is to give the direction of prediction model correction. Therefore, MPC optimization is not only model-based optimization, but also a closed-loop optimization to improve the model. Greatly improves the control accuracy of MPC. Enhance the actual adaptability of the control object.

For example, a fairly common prediction error can be described as (1.40).

$$e(k+1) = y(k+1) - \hat{y}(k+1) \tag{1.40}$$

By adopting a weighted method to correct the predicted value at the next moment, the following results can be obtained as shown in (1.41).

$$\tilde{Y}_p = Y_p + he(k+1) \tag{1.41}$$

where $\tilde{Y}_p = [\hat{y}(k+1), \hat{y}(k+2), ...]^T$ is the system output predicted at the sampling point $t = (k+1)T$ after error correction; $h = [h_1, h_2, ...]$ is the error weighting coefficient.

After correction, the initial predicted value at the next sampling time is obtained. Since the initial predicted value of the moment is used to predict the system output value of the moment, the initial predicted value of the ext sampling moment is shown in (1.42).

$$\begin{cases} y_0(k+i) = \tilde{y}(k+i+1) + h_{i+1}e(k+1) \\ y_0(k+p) = \tilde{y}(k+p) + h_p e(k+1) \end{cases} \tag{1.42}$$

The closed-loop negative feedback of the system is constructed by error correction. The closed-loop negative feedback can improve the stability of the system and improve the system performance and control precision.

1.5 Conclusion

The energy management strategy of hybrid electric vehicle is a nonlinear and complex optimization problem. Researchers began to formulate the rule-based control strategy to solve this problem. Rule-based energy management strategy has the characteristics of simple and good implementation. Therefore, it is widely used in the development of vehicle control strategy. However, its adaptability to different driving cycles varies greatly because of the single control strategy. The logic threshold of control strategy should be calibrated repeatedly according to engineering experience and expert knowledge when making control strategy according to different working conditions. It is costly and difficult to achieve optimal control effect of energy management. With the development of hybrid electric vehicle technology, the rule-based control strategy has been difficult to ensure the optimal system efficiency. Therefore, researchers use the optimal control technology and keep improving it. Although good results have been achieved, the design needs to rely on known driving cycles, and it cannot be guaranteed to be optimal in other driving cycles. With the improvement of microprocessor performance, real-time optimal control strategy based on driving cycle prediction has become a research hotspot. However, the difficulty of this strategy is to predict driving states. With the development of intelligent transportation technology, the prediction of future vehicle state will be more and more accurate, which solves the difficulty of model predictive control. Therefore, model prediction combined with intelligent transportation technology will become a research hotspot.

References

1. S.H. Mohr, Ward J, Ellem G, et al., Projection of world fossil fuels by country. Fuel (2015)
2. S. Sorrell, J. Speirs, R. Bentley et al., Global oil depletion: a review of the evidence. Energy Policy **38**(9), 5290–5295 (2010)
3. M. Kebriaei, A.H. Niasar, B. Asaei, Hybrid electric vehicles: an overview, in *2015 International Conference on Connected Vehicles and Expo (ICCVE)* (IEEE, 2016)
4. S.G. Wirasingha, A. Emadi, Classification and review of control strategies for plug-in hybrid electric vehicles. IEEE Trans. Veh. Technol. **60**(1), 111–122 (2011)
5. K.T. Chau, Y.S. Wong, Overview of power management in hybrid electric vehicles. Energy Convers. Manage. **43**(15), 1953–1968 (2002)

6. T. Lundberg, J. Persson. Hybrid powertrain control—a predictive real-time energy management system for a parallel hybrid electric vehicle (2008)
7. J. Park, J. Oh, Y. Park, et al. Optimal power distribution strategy for series-parallel hybrid electric vehicles, in *International Forum on Strategic Technology* (IEEE, 2007)
8. K. Ahn, P.Y. Papalambros, Engine optimal operation lines for power-split hybrid electric vehicles. Proc. Inst. Mech. Eng., Part D: J. Automob. Eng. **223**(9), 1149–1162 (2009). https://doi.org/10.1243/09544070J-AUTO1124
9. Y. Cheng, K. Chen, C.C. Chan, A. Bouscayrol, S. Cui, Global modeling and control strategy simulation for a hybrid electric vehicle using electrical variable transmission, in *2008 IEEE Vehicle Power and Propulsion Conference*, Harbin (2008), pp. 1–5. https://doi.org/10.1109/VPPC.2008.4677794
10. M. Schulze, R. Mustafa, B. Tilch et al., Energy management in a parallel hybrid electric vehicle for different driving conditions. Sae Int. J. Alternat. Powertrains **3**(2), 193–212 (2014)
11. H.I. Dokuyucu, M. Cakmakci, Concurrent design of energy management and vehicle traction supervisory control algorithms for parallel hybrid electric vehicles. IEEE Trans. Veh. Technol. **65**(2), 555–565 (2016)
12. W. Shabbir, S.A. Evangelou, Exclusive operation strategy for the supervisory control of series hybrid electric vehicles. IEEE Trans. Control Syst. Technol. **24**(6), 1–9 (2016)
13. M.L. Zhou, D.K. Lu, W.M. Li et al., Optimized fuzzy logic control strategy for parallel hybrid electric vehicle based on genetic algorithm. Appl. Mech. Mater. **274**, 345–349 (2013)
14. Lu, Dengke, Li, et al., Fuzzy logic control approach to the energy management of parallel hybrid electric vehicles, 592–596 (2012)