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Predictive and Coordinated Power Control Strategy for Series Hybrid Electric Vehicle with Fuzzy Adaptive Filter

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ABSTRACT

The power control strategy (PCS) is a key technology of series hybrid electric vehicle (SHEV) owing to the ability to coordinate the power flow between multi-energy sources to reduce fuel consumption. When power allocation command of PCS fluctuates sharply, engine-generator set (EGS) might not output the power allocated by the PCS in time, due to the dynamic response lag of engine. In this case, it would cause the lack of vehicle driving power. Therefore, how to ensure smooth power output of EGS and obtain the optimal fuel economy is a challenge. To solve this problem, a predictive and coordinated power control strategy for SHEV is proposed in this study. A predictive adaptive equivalent consumption minimization strategy (PA-ECMS) is proposed to optimize power flow in real time, in which long short-term memory network is applied to predict future demand power to adjust the equivalent factor. In order to reduce the fluctuation of power allocation command, an adaptive fuzzy controller is designed to modify the working points of engine according to the optimizing results of PA-ECMS. The results show that the power command of PCS can be smoothed, and the fuel economy can be improved by 4.91% over conventional ECMS.

Keywords: Series hybrid electric vehicle; Power flow control; Long short-term memory; Equivalent consumption minimization strategy; Fuzzy controller

1. INTRODUCTION

As one of the main sources of global warming and energy shortage, the transportation sector needs to introduce new technologies to achieve the purpose of energy conservation and emission reduction [1,2]. The hybrid powertrain, which is equipped with at least two energy sources, is an important technology to reduce fuel consumption and greenhouse gas [3]. Among the different types of hybrid electric vehicle (HEV), series HEV (SHEV) utilizes engine-generator set (EGS) and power battery pack as dual-power sources, and the electric motor as the driving device. The power sources of SHEV are mechanically decoupled from the driving device, the engine can work in the high-efficiency area to reduce fuel consumption. Therefore, SHEV might be one of the most promising configurations. Although the separation of engine and wheels improves its working flexibility, SHEV has higher demand for power control strategy (PCS), which needs to coordinate the power flow and control the operation of engine. Thus, it is necessary to design an efficient PCS to improve the performance of SHEV.

Recently, many studies have been performed on PCS for SHEV. To obtain better fuel economy in real-time applications, equivalent consumption minimum strategy (ECMS) is applied to PCS. ECMS converts electricity consumption and fuel consumption to obtain the minimum instantaneous energy consumption, and the equivalent factor (EF) between the two types of energy consumption has a great influence on the control effect. In Ref. [4], a self-adaptive ECMS (A-ECMS) was proposed to reduce fuel consumption, in which the EF is determined from the historical driving conditions. In Ref. [5], an ECMS-CESO is developed, in which the optimal bound of EF is determined. Moreover, in Ref. [6], an optimization-oriented A-ECMS is proposed, the results show that it has robust performance. Therefore, ECMS is a promising PCS method. However, when ECMS is used for power distribution, the power command might have severe fluctuations. For SHEVs, when the demand power fluctuates sharply, the command of PCS would not be responded by engine in time, due to the limitation of operating characteristics of engine. At this time, the actual output power of EGS would not meet the expected power, which would result in the lack of vehicle power. In order to improve the control effect of ECMS-based PCS for SHEV, the above issue should be considered.

Motivated by this issue, a predictive and coordinated PCS for SHEV is proposed in this study. Firstly, in order to adjust the equivalent factor, a long short-term memory (LSTM) network is applied to predict future demand power. Secondly, a predictive adaptive ECMS (PA-ECMS) is proposed to optimize power flow in real time. Thirdly, to reduce the fluctuation of power allocation command, an adaptive fuzzy controller is designed to modify the working points of engine according to the optimizing results of PA-ECMS.

2. MODEL DESCRIPTIONS FOR SHEV

In this paper, the SHEV is studied, whose powertrain structure is composed of EGS, battery pack, inverter, electric motors and transmission device, as shown in Fig. 1. The vehicle is driven by an electric motor, and the power input into the motor is from the battery pack and EGS. Table 1 introduces the specific parameters of components.

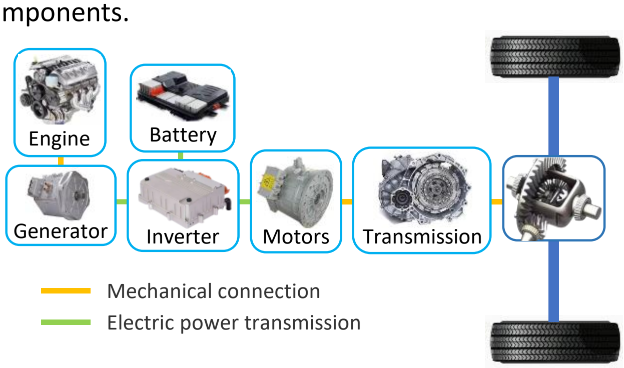

Fig. 1. The structure of SHEV

Table 1. Main parameters of the SHETV

Component	Parameters	Values
Engine	Maximum torque	2080Nm
Generator	Maximum power	880kW
Traction motor	Type	SPMSM
	Maximum power	300kW
Battery	Type	Li-ion
	Capacity	800Ah
	Voltage	600V
Vehicle	Mass	26,000kg

According to the longitudinal dynamics of vehicles, the demand driving power P_{dem} can be expressed as

$$P_{dem} = Mgf_r \cos\theta + Mg \sin\theta + \frac{1}{2} C_D A \rho v^2 + M\frac{dv}{dt} \tag{1}$$

where M is the vehicle mass, g is the gravity acceleration, f_r is rolling resistance coefficient, θ is road angle, C_D is aerodynamic drag coefficient, ρ is air density, A is bus frontal areas and v is vehicle speed.

The instantaneous fuel consumption of the engine can be obtained by looking up the table according to its speed ω_{Eng} and torque T_{Eng}. The speed regulation process of EGS can be expressed as

$$T_{Eng} - T_{Gen} = \frac{\pi}{30}(J_{Eng} + J_{Gen})\frac{dn_{Gen}}{dt} \tag{4}$$

where n_{Gen} and T_{Gen} are the speed and torque of generator, J_{Eng} and J_{Gen} are the rotational inertia of engine crankshaft and generator, respectively.

An equivalent circuit model could be applied to depicted the dynamic characteristic of the power battery pack, and the change of state of charge (SOC) has an important influence on the power flow control, which can be expressed as

$$SOC = SOC_0 - \frac{\int I_{Batt} dt}{Q_{Batt}} \tag{7}$$

$$\frac{dSOC}{dt} = -\frac{V_{oc} - \sqrt{V_{oc} - 4R_{\mathrm{int}} P_{Batt}}}{2R_{\mathrm{int}} Q_{Batt}} \tag{8}$$

where V_{oc} is the open-circuit voltage, I_{Batt} is the battery pack current, Q_{Batt} is the battery pack capacity and P_{Batt} is the output power of battery.

3. PREDICTIVE AND COORDINATED POWER CONTROL STRATEGY FRAMEWORK

In this section, a predictive and coordinated power control strategy is presented, whose diagram is shown in Fig. 2. The proposed strategy can be described as three steps. In the first step, the time-series data of vehicle historical speed is used as input to LSTM neural network to predict the corresponding future time-series data. In the second step, an PA-ECMS is proposed to adjust EF and optimize the power flow. In the third step, a fuzzy adaptive filter is applied to ensure the output power of EGS according to the power distribution result. The detailed description is presented below.

3.1 Demand power prediction based on LSTM network

The future demand power can be indirectly obtained by speed according to Eq. (1). As an improved recursive neural network, LSTM neural network has unique advantages in processing time series data because it can associate historical data through short-term and long-term memories. Therefore, compared with other methods, LSTM could predict the change of vehicle speed and acceleration more accurately.

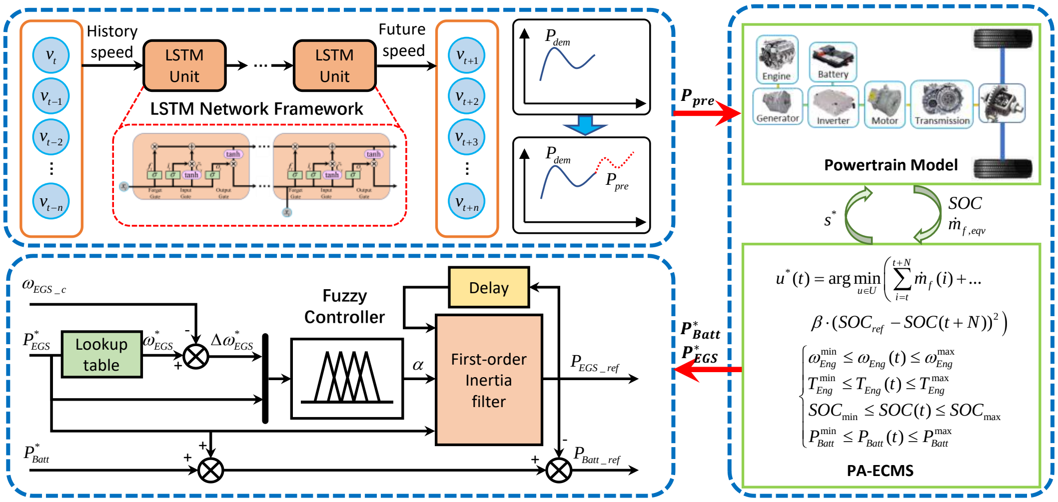

Fig. 2. Schematic of the proposed strategy

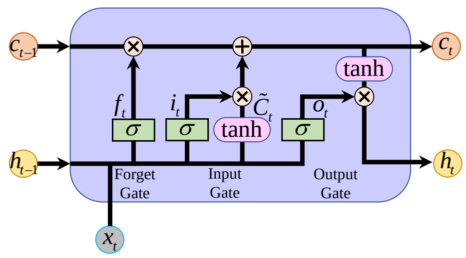

Fig. 3 Processing framework of LSTM block

A LSTM block consists of a memory cell and three gates including the input, output and forget gates. The memory cell can control the transmission of information to the next moment, and three gates control the flow of information into and out of the memory cell. The processing framework of a LSTM block is shown in Fig.3. In this paper, the historical vehicle speed sequence is the input of LSTM network, which is updated over time. The output is the future speed sequence.

3.2 Power Flow control based on PA-ECMS

According to the idea of ECMS, instantaneous equivalent fuel consumption in the process of vehicle driving can be expressed as

$$\dot{m}_{f,eqv}(t) = \dot{m}_f(t) + \dot{m}_{ress}(t) = \dot{m}_f(t) + s \cdot P_{Batt}(t) / Q_{lhv}$$

The optimal fuel economy of the whole driving cycle can be achieved by seeking the minimum value of instantaneous equivalent fuel consumption at each moment. It can be found that the control effect of ECMS depends on EF, thus, the EF needs to be adjusted in time. In this paper, the EF is optimized and updated in predicted time horizon of LSTM. The cost function of the optimization of EF is given as

$$u^*(t) = \arg\min_{u \in U} \sum_{i=t}^{t+N} \dot{m}_f(i) + \beta \cdot (SOC_{ref} - SOC(t+N))^2$$

The purpose of the cost function is to adjust EF to minimize fuel consumption and maintain SOC within demand range in the optimization domain. Finally, the optimal power allocation between EGS and battery pack is obtained under optimal EF.

3.3 Engine working points correction method

For SHEVs, the engine has many working methods to meet demand power. Thus, it works along the optimal working curve to reduce fuel consumption in this paper. However, engine working along the optimal working curve needs frequent speed regulation. When the demand power of vehicle increases suddenly, EGS might not produce the expected power allocated by PCS, due to the limitation of operation characteristic of engine. Therefore, a fuzzy adaptive filter (FAF) is applied to modify the result of power allocation.

The input of fuzzy controller is the expected power and deviation of rotate speed of EGS, the output is the filter coefficient. The first-order inertia filter can be expressed as

$$P_{EGS\_ref}(t) = \alpha \cdot P^*_{EGS}(t) + (1-\alpha) \cdot P_{EGS\_ref}(t-1)$$

4. SIMULATION RESULTS AND DISCUSSION

In this paper, the simulation test driving cycle is composed of highway fuel economy test cycle (HWFET) and real-world driving cycle, as shown in Fig. 4.

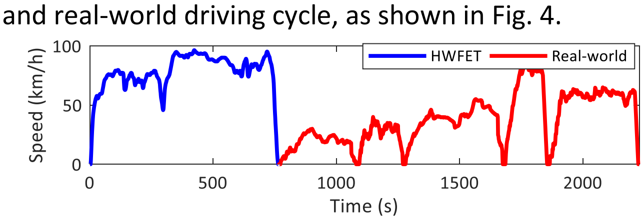

Fig. 4. The test driving cycle

In order to reduce the computational complexity, future demand power is predicted and EF is optimized every 5s. The Speed predicted result based on LSTM network is shown in Fig. 5. It can be found that the predicted speed in the next 5s is close to future speed, which illustrates that the LSTM network has a good performance in speed prediction.

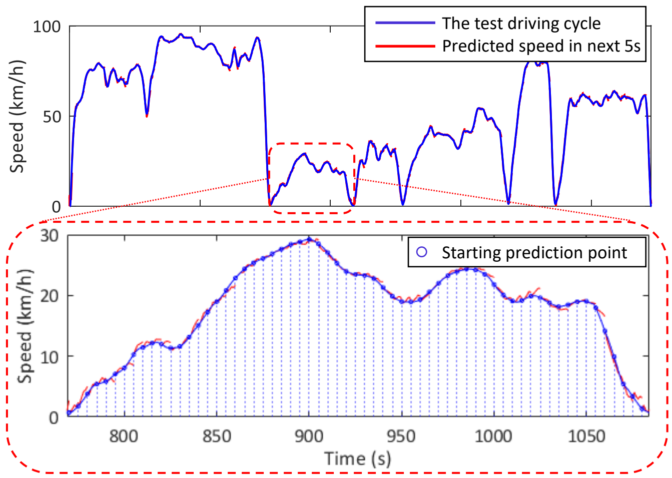

Fig. 5. Speed prediction based on LSTM network

The trajectories of EF and SOC under the test driving cycle is shown in Fig. 6. It can be seen that the EF changes with the optimization results, and when the demand power is high, EF increases to ensure that the battery SOC is within the allowable range. Moreover, as can be seen from the trajectory of SOC, the battery is constantly charging and discharging to assist the engine work in the high-efficiency area. Besides, Fig. 7 illustrates the effect of FAF, where the power of EGS is smoothed with FAF. Therefore, the fuel economy of the proposed method is improved compared to conventional ECMS and PA-ECMS without FAF, as shown in Table 2.

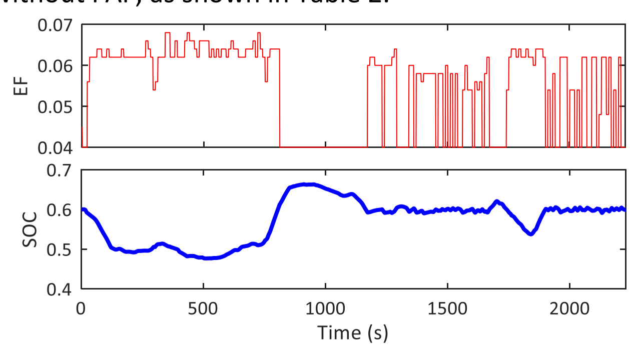

Fig. 6. The trajectories of EF and SOC

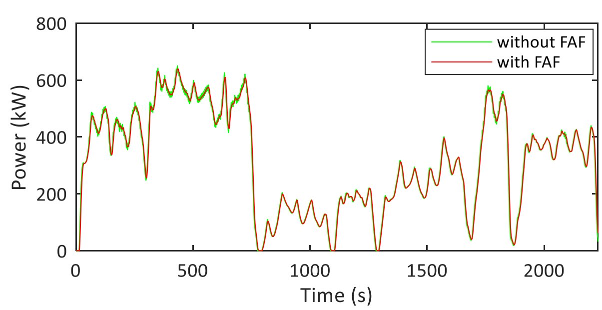

Fig. 7. The effect comparison of FAF

Table 2. Comparison results

Method	Fuel consumption (L)	Final SOC
ECMS	58.76	0.602
PA-ECMS	57.04	0.598
PA-ECMS+FAF	55.87	0.601

5. CONCLUSION

In this paper, a PA-ECMS considering dynamic response of EGS for SHEV is proposed. In order to adjust the equivalent factor, a LSTM network is applied to predict future demand power. PA-ECMS is proposed to optimize power flow in real time. To reduce the fluctuation of power allocation command, an adaptive fuzzy controller is designed to modify the working points of engine according to the optimizing results of PA-ECMS. The results show that the power command of PCS can be smoothed, and the fuel economy can be improved by 4.91% over conventional ECMS under the combined test driving cycle.

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