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Shared Control Based Energy Management Strategy for Hybrid Electric Vehicle Taking into Account Demand Power Optimization

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Abstract

To further explore the potential of fuel economy for hybrid electric vehicle (HEV), a shared-control-based energy management strategy (SCEMS) with four modules of the human-vehicle closed-loop system, reference power calculation, driver power distribution, and shared control strategy is proposed. The SCEMS possesses three innovations. Firstly, the rational driver's power demand is considered to achieve optimal fuel consumption. Secondly, a dimensionality reduction strategy of two-dimension DP algorithm is proposed for online application. Finally, based on the shared control and the intelligent traffic system (ITS) a game mechanism between driver and controller is constructed to adapt to different driving styles and road conditions. In the human-vehicle closed-loop system, a model is built, combining the driver model with a longitudinal dynamic model, to optimize the power demand and power distribution. In the reference power calculation, the dynamic programming (DP) algorithm is utilized to produce the optimal power of a future forward road segment based on the ITS. The time complexity of DP algorithm is reduced by a state of charge (SOC) table looked up online derived from neural network and road condition identification. In the driver power distribution, the original demand power is assigned to the engine and motor. In the shared control strategy, two condition description equations are respectively constructed to indicate the fuel consumption rate of the engine and the efficiency of the motor, and then two adjustment curves are fitted to regulate the proportion of driver and controller to improve the power-wasting and ineffective behaviors. The problem of driving style and emergency road condition adaptation is settled depending on the cumulative-error-based weight adjustment strategy.

Introduction

Plug-in Hybrid Electric Vehicle (PHEV) can obtain electric energy from the external power grid through charging, and its strategy is to consume electricity to the lower limit within the determined range of travel, reduce part of the fuel consumption, and adjust the engine to work in the high-efficiency area. The EMS of PHEV is mainly divided into optimization-based strategy and rule-based strategy. With the development of new technologies such as the internet of vehicles, some new strategies have also emerged. Optimization-based EMS refers to strategies that use optimization algorithms to solve solutions, mainly including DP, PMP, and GT. C. Romaus et al. [1] have presented a strategy to control power distribution with DP based on consideration of traffic conditions and random effects of drivers. The rule-based energy management strategy has become the first choice for practical engineering applications due to its simple structure, small computational complexity, and low memory footprint, mainly including CDCD and NN. To overcome the shortcomings of NN, literature [2] has proposed a control rule to extract the optimal solution of multiple typical working conditions and a strategy of selecting corresponding rules based on working condition identification in the online application. With the rapid development of ITS centered on intelligent network technology, the traditional EMS has gained new vitality. Reference [3] has proposed a PHEV energy management system based on vehicle-vehicle, vehicle-road communication system, and cloud computing for vehicle speed prediction. For different application scenarios such as intersections, the author uses the obtained surrounding vehicle and traffic light information, combined with the car following model to predict the future speed of the vehicle. The prediction algorithm adopts an improved chain NN taking the prediction result of the previous step as one of the inputs of the next prediction, which is similar to the idea of a recursive network, and the prediction accuracy is greatly improved. Finally, according to the guidance of future road condition information, the equivalent factor of the ECMS strategy is adjusted in real-time. Compared with the traditional adaptive ECMS, the economy of this strategy is improved by about 5%. Ozatay E et al. [4] have proposed a cloud computing-based optimal vehicle speed assistance decision system for HEV. The working condition information of a future road is obtained through the ITS system, and the optimal vehicle speed is calculated by the DP algorithm in the cloud server, which is sent to the driver through the visualization system, and the driver operates the vehicle according to the speed prompt. At the same time, the authors have designed an adaptive strategy, which is similar to the reinforcement learning algorithm, judges the driver's attitude according to the error between the actual speed and the reference speed, and adjusts the optimal range of the reference speed in the next calculation cycle. Through the real vehicle experiment, it is found that when the driver completely follows the reference speed, the fuel-saving can be achieved by 14.1% under high-speed conditions and 7.4% under urban conditions.

This paper is organized as follows. Firstly, a powertrain model of PHEV is constructed. Secondly, based on a PHEV, the driver is incorporated into the closed-loop system as a control node, and a human-vehicle closed-loop model is established. On this basis, a generalized energy management strategy aiming at optimizing power demand and optimizing power distribution is proposed. Thirdly, Aiming at the shortcomings of the poor adaptive ability of the rule-based strategy, a shared-control-based EMS is proposed to solve the problem of adaptive driving style and control authority. Based on the ITS system, the DP algorithm is computed in the cloud server to calculate the optimal control rules, and then sent to the vehicle as to the reference input of the controller. According to the energy consumption level of the driver's operation, the proportion of the controller input and the driver's input is adjusted. A driver model considering the influence of controller input is established based on MPC. To meet the requirement of real-time control, a dimensionality reduction strategy of two-dimensional DP is proposed. To adapt to the driving styles of different drivers, a weight adjustment strategy based on the cumulative error of driver input is designed. Finally, a test driving cycle is selected to verify the performance of the strategy

This paper has three contributions. First, the rationality of the driver's demand power is considered to tap the fuel-saving potential of the PHEV. Second, the global optimization is transformed into segmented optimization using future road information. Although the solution is sub-optimal, it is more practical based on real-time working conditions. Third, a human-computer interaction mechanism is established to realize the controllability of control authority. The degree of intervention of the controller can be adjusted according to the driving style of different drivers.

Vehicle Modeling Setup

Vehicle Architecture

The research object of this paper is a PHEV commercial logistics vehicle including the engine, motor, clutch, gearbox, and battery. The vehicle is a typical coaxial parallel model as shown in Figure 1 and can work in motor drive mode, engine drive mode, hybrid drive mode, idle mode, and braking mode. Some vehicle characteristics are depicted in Table 1.

FIGURE 1 Vehicle configuration.

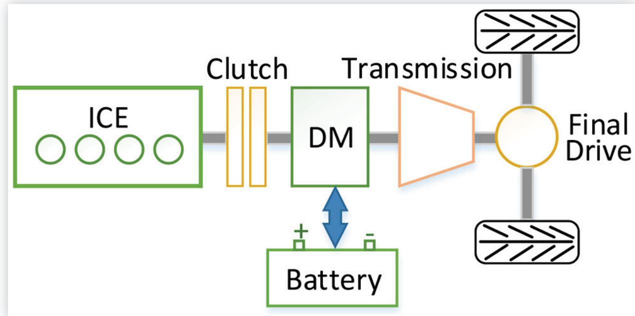


TABLE 1 Vehicle components parameters.

M (vehicle mass)	3800 kg
f_r (rolling resistance)	0.008
A (frontal area)	3.28 m^2
C_D (air drag coefficient)	0.362
g (gravity acceleration)	9.8 m/s^2
R (tire radius)	0.34m
i_0 (final drive ratio)	4.889
δ (rotating mass conversion coefficient)	1.03
i_g (gear ratio)	4.065/2.371/1.157/0.853/0.674

Vehicle Longitudinal Dynamics Model The energy management problem focuses on fuel economy, so the traditional longitudinal model is selected to characterize the transmission characteristics of the vehicle, and the lateral dynamic features are left out. The vehicle longitudinal dynamics equation is written as follows:

$$\frac{Ti_g i_0 \eta_T}{R} = Mgf_r + \frac{C_D A(3.6v)^2}{21.15} + \delta M\dot{v} \quad (1)$$

where T is torque, η_T is drivetrain efficiency, v is velocity.

Engine Model This paper mainly focuses on the fuel consumption of the engine. Therefore, the model is established based on the fuel consumption characteristics map as shown in Figure 2. The engine fuel consumption rate can be written as follows:

$$\dot{m}_f = f\left(P_e,\ n_e\right) \quad (2)$$

where P_e is engine power, n_e is engine speed.

Motor Model The vehicle uses a permanent magnet synchronous motor, which can work in charge mode and discharge mode. The motor efficiency is described in Figure 3, and output power can be written as follows:

$$P_m = \begin{cases} P_m' \eta_m, & P_m' > 0 \\ P_m' / \eta_m, & P_m' < 0 \end{cases} \quad (3)$$

where P_m is motor output power, P_m' is motor total power, η_m is motor efficiency.

FIGURE 2 Engine fuel consumption characteristics map.

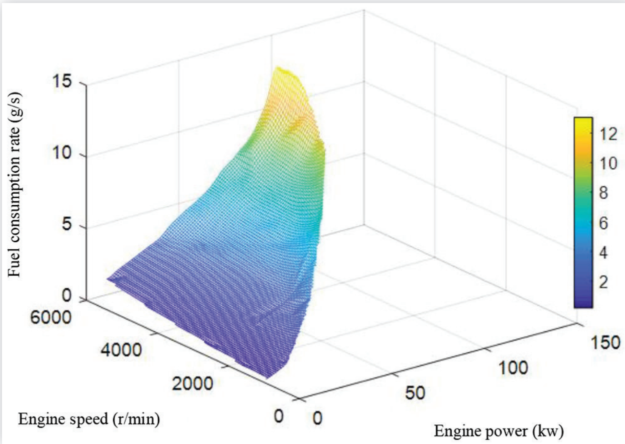
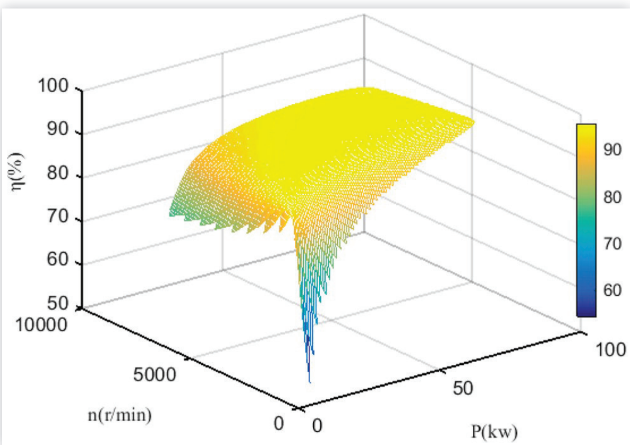


FIGURE 3 Engine fuel consumption characteristics map.



Battery Model The energy management strategy (EMS) used in this paper does not involve the changing relationship between SOC and the internal voltage and current of the battery. It only needs to obtain the change of battery energy storage and SOC through battery power integration. Some battery characteristics are depicted in Table 2.

TABLE 2 Battery components parameters.

Bus nominal voltage	256 V
Battery pack capacity	50 Ah
Maximum SOC	100%
Minimum SOC	20%
Average discharge efficiency	95%
Average charging efficiency	95%

Human-Vehicle Closed-Loop System

In the human-vehicle closed-loop system, the driver feels the state of vehicle through his sensory system, identifies the surrounding working conditions, compares the current driving state with the reference state established in the brain, and then controls the motion system to drive the vehicle. According to the driver's control instructions, including the accelerator pedal, brake pedal, and gear, the vehicle transmits the driving force or braking force through the transmission system and then accelerates or decelerates.

Human-Vehicle Longitudinal Dynamics Model

The human-vehicle longitudinal dynamics model can be written as follows:

$$\begin{cases} P_{dem} = f\left(v, \quad v_{ref}\right) \\ P_{dem} = \dfrac{3.6v}{\left(0.377\times 9550\right)\eta_T}\left(Mgf_r + \dfrac{C_D A\left(3.6v\right)^2}{21.15} + \delta M\dot{v}\right) \end{cases} \tag{4}$$

where P_{dem} is driver demand power, v_{ref} is driver reference velocity, f is process by which the driver controls the vehicle based on the vehicle velocity and the reference velocity.

Generalized Energy Management Strategy

The traditional EMS is to reasonably allocate the required power to the engine and motor according to the driver's intention and road environment during the driving process of the PHEV, to achieve the purpose of reducing fuel consumption and emissions. The traditional EMS is an open-loop optimal solution problem under the premise of fully satisfying the required power, and the optimization index is the lowest fuel consumption. According to the human-vehicle longitudinal dynamics model, the driver is an important part of the closed-loop system. The rationality of the driver power demand must be considered to obtain optimal fuel consumption. Therefore, the driver demand power should be incorporated into the optimization process to establish a generalized energy management strategy (GEMS). In this strategy, two issues need to be considered: whether the driver demand power is reasonable, and how the demand power is distributed. The GEMS can be written as follows:

$$\begin{cases} P_{dem} = P_e + P_m \\ min\sum_{1}^{N}\dot{m}_f\left(P_{dem,} \quad P_{e,} \quad n_e\right)\Delta d \end{cases} \tag{5}$$

where Δd is sampling distance.

strategy. The driver's initial reference speed is 20km/h. The initial weight is 0.5. The driver changes the original driving habits for some reason at point A, which is reflected in the picture to change the reference speed to 30km/h. The driver's control amount will deviate from the original reference trajectory, and there will be an error between the estimated driver's control amount and the cumulative error will gradually increase. When the cumulative error reaches the upper limit at point B, the weight is adjusted to 0.2 to increase the proportion of driver input. The driver changes back to the original reference speed at point C, and the accumulated error gradually decreases. The cumulative error is reduced below the threshold at point D, and the weight is adjusted to 0.5.

Simulation Verification

Based on a desktop workstation, the computing function of the cloud server is simulated. Assuming that the remote uplink and downlink communication process is timely and reliable, the communication part can be ignored during simulation. The distance between vehicles is 10 meters. To facilitate the comparison and verification, the EMS adopts the DP algorithm. The calculation result is shown in Figure 12. Since the optimization process is based on the average vehicle speed, the reference vehicle speed shape is quite different from the original vehicle speed, and due to the segmentation optimization, some segments are not optimal relative to the whole. However, the computation time is reduced by 65.87% compared to the two-dimensional DP algorithm.

The weight of the engine and motor is shown in Figure 13. In the middle and low speed stage, the weight of the engine takes alternate values, and there is no obvious tendency. The weight of the motor is concentrated around 0.8, and more controller control is used, indicating that the driver's operation at this time will lead to lower motor efficiency. In the middle and high speed stage, the engine weight is concentrated around 0.2, indicating that the driver's operation is more reasonable, and the authority is gradually withdrawn from the controller. The weight of motor takes values alternately, and there is no obvious tendency.

The position of the engine working points is shown in Figure 14. Part of the work points are transferred to the high-efficiency area, which can achieve performance improvement. But some working points are not handled better because the acquisition of the reference vehicle speed is not globally optimal, and the lower limit is set when the weight is adjusted. The driver is always in the loop and its poor control behavior will also have an impact on the improvement of the economy. The control results are listed in Table 3. Compared with the traditional global optimization strategy based on the DP algorithm, the strategy achieves a 1.97% economic improvement. Compared with the rule-based strategy, although the economic improvement is lower, its theoretical design is more reasonable, the situation is more comprehensive, and it has more practical value.

FIGURE 12 Optimization result.

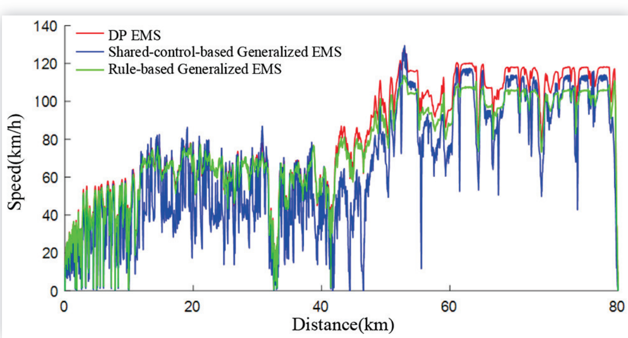


FIGURE 13 Weight value.

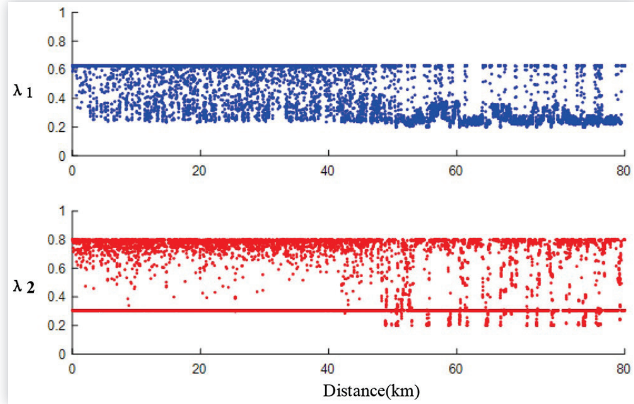


FIGURE 14 The engine working points.

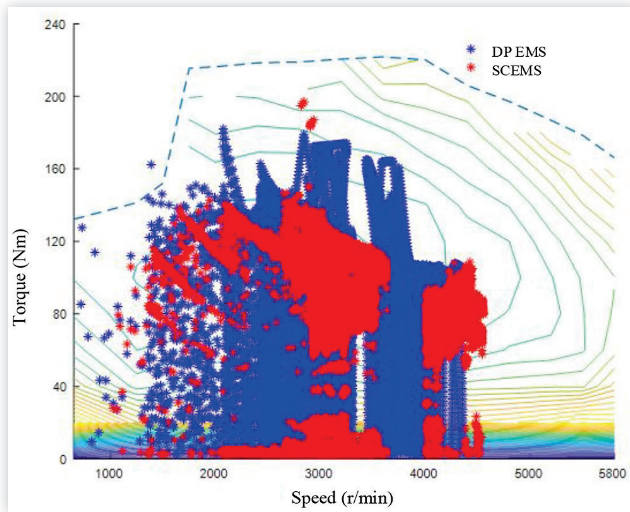


TABLE 3 Engine fuel consumption of the control strategies.

Control strategy	Fuel consumption	Improvement
DP EMS	6.99 L	-
Rule-based Generalized EMS	6.59 L	5.76%
Shared-control-based Generalized EMS	6.86 L	1.97%

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Definitions/Abbreviations

PHEV - plug-in hybrid electric vehicle
SCEMS - shared-control-based energy management strategy
EMS - energy management strategy
ITS - intelligent traffic system
DP - dynamic programming
NN - neural network
SOC - state of charge
PMP - pontryagin's minimum principle
GT - game theory
CDCS - Charge-Depleting Charge-Sustaining

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