ENERGY MANAGMENT STRATEGY FOR PLUG-IN HYBRID ELECTRIC VEHICLES BASED ON SOC PLANING

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In order to further improve the fuel economy of plug-in hybrid electric vehicles (PHEV), a SOC trajectory tracking strategy based on LSTM global speed prediction is proposed. First, based on the Pytorch deep learning framework, an LSTM model for global vehicle speed prediction in the spatial domain is established. Second, based on the relationship between the battery power consumption and the speed and acceleration per unit time, a global SOC trajectory planning method is designed. Third, a regular SOC trajectory tracking strategy is established to allow the vehicle to distribute the torque between the engine and motor based on real-time SOC feedback from the battery. Finally, the fuel economy comparisons are made between the Charge Depleting-Charge Sustaining (CD-CS) energy management strategy, the SOC linear decrement-based energy management strategy and the SOC planning based-energy management strategy under 3x, 4x and 5x field driving cycles. The simulation results show that compared with the other two strategies, the SOC planning based-energy management strategy can improve the fuel economy by about 7.67% to 8.99%.

Keywords: Plug-in hybrid electric vehicles (PHEV); energy management strategies; SOC planning; LSTM vehicle speed prediction

1. Introduction

Energy management strategy is a key technology to improve the fuel economy of hybrid vehicles. Correct energy management strategies should reduce the fuel consumption as much as possible while maintaining vehicle dynamics [1]. The CD-CS strategy is the most basic energy management strategy. When the electric energy is not enough to support the vehicle to drive to the destination, the motor drive is first used, and then engine drive is applied [2]. This strategy is simple and easy to calculate, but the determination of its rules often relies on a large number of calibration data and expert experience. The same set of rules is difficult to adapt to complex and changeable driving cycles, and the migration adaptability is poor. Therefore, finding a more adaptable real-time energy

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management strategy is an important topic in new energy vehicles [3]. With the development and popularization of 5G and intelligent transportation systems (ITS), integrating energy management strategies with traffic information has become a hop spot [4-8]. Among them, using the traffic information to plan the SOC trajectory of plug-in hybrid vehicles, and combining the real-time feedback of the actual SOC of the battery to allocate the torque of the engine-motor is an important idea to realize such strategies [9-10]. Sun obtained the traffic information such as section length, average speed, average acceleration, and acceleration standard deviation for each road section from ITS. Then combined with Markov speed prediction, the time-domain SOC trajectory in the MPC energy management strategy is planned. Finally, compared with DP, MPC and other strategies, the effectiveness of this strategy was verified [11]. Wang used the congestion level of each road segment obtained in the ITS for vehicle speed prediction, and then allocated the available battery power in units of road segments. Current road segment speed prediction is provided with more traffic information, such as the distance and speed of the vehicle ahead. The combined road segment power can be used for SOC trajectory planning, which improved the fuel economy by 15% compared to the CD-CS strategy [12]. Zhao obtained the global vehicle speed information through ITS, and used the DP algorithm for SOC trajectory planning. Compared with the strategy without traffic information, this strategy reduced the travel cost by 0.3904 yuan on the route between Chongqing University and Changan Ford [13].

Based on the above analysis, this paper proposes a SOC planning based-energy management strategy for parallel plug-in hybrid electric vehicles with P2 configuration. First, based on Matlab/Simulink, a single-axis parallel hybrid vehicle model is established to provide a basis for proposing and verifying energy management strategies. Second, the field traffic information from Qingdao University of Technology to Qingdao Huanghai College was collected. The on-site traffic model was established using the micro-traffic simulation software VISSIM, and the obtained traffic information was used as the dataset for the long-short-term memory network (LSTM) vehicle speed prediction model. Then, based on the Pytorch deep learning framework, a spatial domain global speed prediction model based on roadside infrastructure is established. A global SOC planning method based on the relationship between battery power consumption per unit time and the vehicle speed and acceleration is proposed. Finally, a regular SOC trajectory tracking strategy is constructed, and its effect on vehicle fuel economy is verified under different on-site driving cycles.

2. Modeling of plug-in hybrid electric vehicle

The structure of a plug-in single-axle parallel hybrid vehicle is shown in

Fig.1.

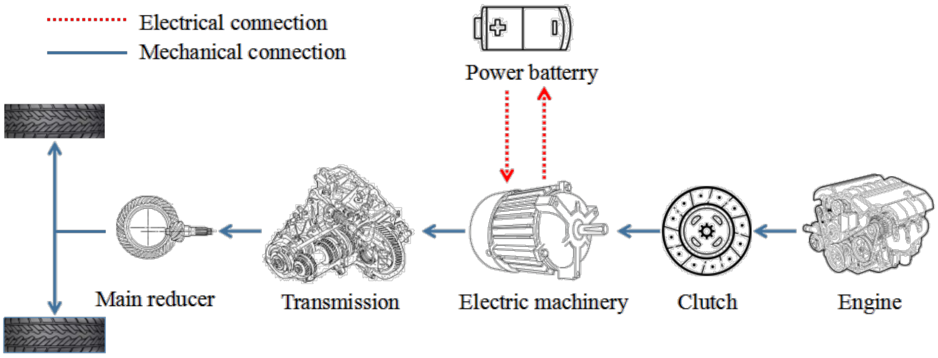

Fig.1 Structure diagram of the plug-in hybrid electric vehicle

The engine and motor are located on the same shaft, with the power decoupled in the middle through the clutch. The motor is mechanically and electrically connected to the engine and the power battery through the inverter. The motor couples the power from the engine and battery and transmits it to the drive through the final drive gear.

The vehicle parameters of the single axle parallel hybrid electric vehicles are shown in Table1.

Table 1

Parameters of the single-axle parallel hybrid electric vehicle

Parameters	Values
Vehicle quality /kg	1550
Wheel radius /m	0.275
Moment of inertia	1.200
Peak engine power/kw	49.920
Maximum motor current /A	400
Minimum voltage of motor /V	60
Transmission ratio of power train	11.1066, 5.6175, 3.5310, 2.7606, 2.2791
Single battery capacity /Ah	17.900
Air density/(kg.m^{-3})	1.200
Air drag coefficient	0.250
Pavement friction coefficient	0.018

3. Global SOC planning based on LSTM

SOC trajectory planning allows the vehicle to precisely reach a lower SOC limit for a set of remaining battery charges at the end of the drive, so as to take full use of the battery capacity of plug-in hybrids. For the most common planning method to reduce the battery SOC linearly over time, it is only necessary to predict the driving distance in advance. However, this method does not consider the influence of driving cycle on the SOC planning trajectory, which is not in line with the actual situation. A reasonable global SOC trajectory planning should predict the driving cycle of the whole travel. With the maturity of electronic maps and ITS, relying on the roadside infrastructure of intelligent transportation, it is possible to perform full speed prediction in the spatial domain. However, ITS are still in the research and development stage, and this paper uses VISSIM instead of ITS to obtain the traffic information.

3.1 Access to field traffic information

This paper investigates and collects traffic information between Qingdao University of Technology and Qingdao Huanghai College. The target route has 10 intersections and 4 T-intersections, with a total length of about 12km. According to the site survey, the input rate in the model is 0.918 for small vehicles, and 0.072 for large vehicles (including buses and vans). Taking 32400s as the simulation time and 324 as the random seed, the model is simulated. The simulation results are shown in Fig.2.

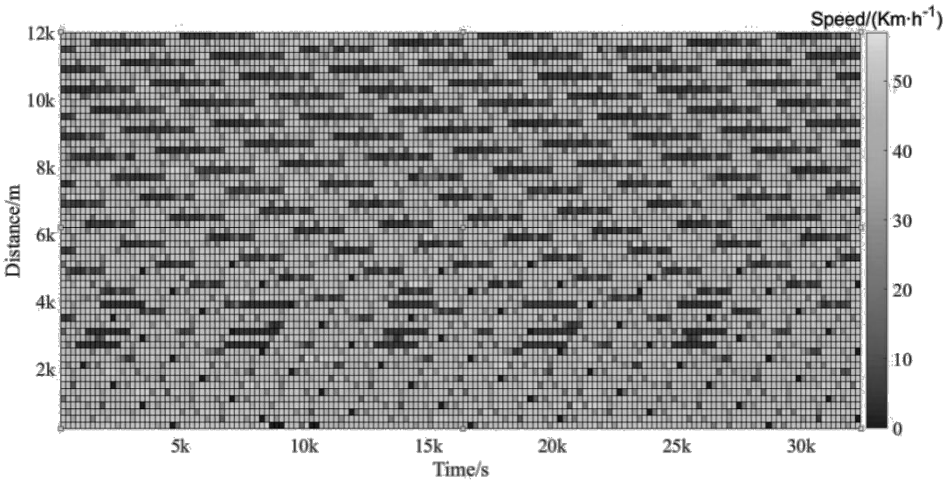

Fig.2 vehicle speed Map

The dark in Fig.2 is low-speed areas. Each dark line corresponds to a congestion point, and the length of the dark line is proportional to the length of the vehicle queue. It can be seen from Fig. 2 that the spatial and temporal distribution of the traffic flow has an obvious signal control law. The VISSIM model established in this section is consistent with the actual road conditions and can be used for subsequent studies.

3.2 Speed prediction based on LSTM

Recurrent neural networks (RNNs) are good at dealing with time series models, which have a structure for storing information and can be computed once to provide information in the next time or future [14]. Furthermore, LSTMs have multiple gating units within their neurons, which can well control the gradient flow and solve the gradient scattering and gradient explosion problems inherent in RNNs [15]. The formula for the LSTM prediction model is as follows:

$$\begin{cases} \tilde{C}^{<t>} = \tanh(W_c[a^{<t-1>}, x^{<t>}] + b_c) \\ \Gamma_u = \sigma(W_u[a^{<t-1>}, x^{<t>}] + b_u) \\ \Gamma_f = \sigma(W_f[a^{<t-1>}, x^{<t>}] + b_f) \\ \Gamma_o = \sigma(W_o[a^{<t-1>}, x^{<t>}] + b_o) \\ C^{<t>} = \Gamma_u * \tilde{C}^{<t>} + \Gamma_f * C^{<t-1>} \\ a^{<t>} = \Gamma_o * \tanh C^{<t>} \end{cases} \tag{1}$$

where, $\tilde{C}^{<t>}$ is the candidate memory unit; $C^{<t-1>}$ is the memory unit at time t-1; $C^{<t>}$ is the updated value of t time memory unit; $x^{<t>}$ is the input vector at time t; $a^{<t-1>}$ is the hidden layer vector at time T-1; $a^{<t>}$ is the hidden layer at time t; Γ_u is the input gate at time t; Γ_f is the forget gate at time t; Γ_o is the output gate at time t; W_c, W_u, W_u and W_o are the corresponding gating weights used for update, respectively; b_c, b_u, b_f and b_o are the deviation items, respectively.

In the spatial dimension, the total length of the line is 12km.Data collectors are set every 200m, and total 60 sets of data are available. In the temporal dimension, the simulation duration is 32,400s, and the data is collected at 200s intervals. Therefore, total 162 sets of data are available. To improve the training accuracy, the training and validation sets were interpolated separately. Since the input vector is a one-dimensional sequence, randomization at the beginning is initialized to prevent over fitting of the prediction model. The model is iterated and tested, and hyperparameters are adjusted in the dataset using mean squared error (MSE Loss) as the loss function. The adjusted hyperparameters are shown in Table2.

Table 2

Hyperparameters of LSTM speed prediction model

Hyperparameters	Value
GRU network layers	3
Number of hidden layer neurons	5
Optimization function	Adam
Input vector length	200
Learning rate	0.1

Taking the data collection point as the unit, combining the vehicle speed and distance of each data collection point predicted by LSTM at the next moment, the global predicted vehicle speed in the spatial domain can be obtained. The comparison between the global predicted vehicle speed and the actual vehicle speed is shown in Fig.3.

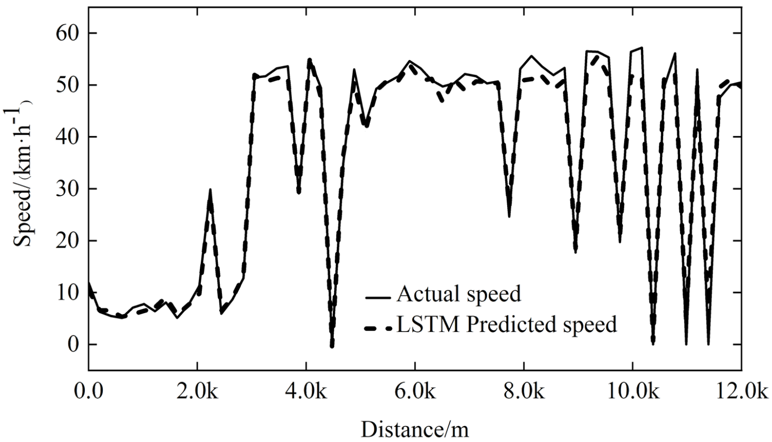

Fig.3 Comparison of predicted speed and actual speed

RMSE value of the predicted vehicle speed is 2.172; MAE value is 1.670, and R^2 value is 0.989. The prediction error of LSTM is about 2m/s, which can meet the requirements of later SOC planning for speed prediction accuracy.

3.3 SOC planning

The field driving cycle in Fig.2 was chosen for SOC planning, with a length of 12 km and a time of 1346s. Velocities and accelerations under field conditions are shown in Fig.4.

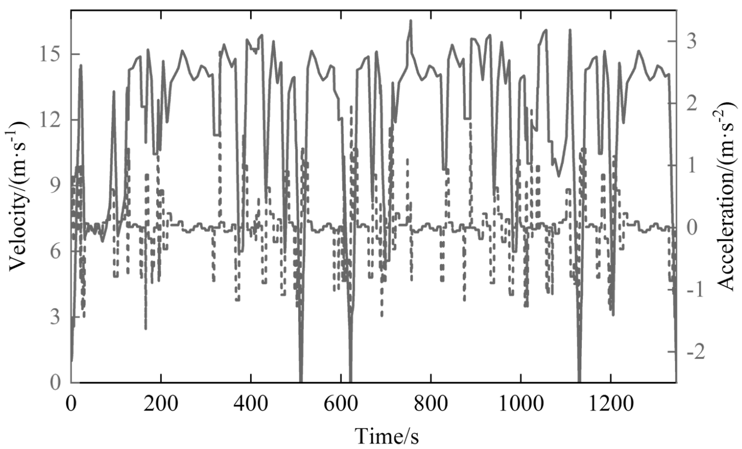

Fig.4 Vehicle speed and acceleration in field driving cycle

Since the influence weights of velocity and acceleration on the final SOC planning trajectory are unknown, a power distribution factor s is introduced to coordinate the influence of velocity and acceleration on SOC. Then the calculation formula of the electrical energy consumption per unit time ΔSOC based on the velocity and acceleration is:

$$\Delta SOC(k) = s \cdot \Delta SOC\_v(k) + (1-s) \cdot \Delta SOC\_a(k) \tag{2}$$

The larger s, the greater the proportion of velocity in the overall SOC trajectory planning. The smaller s, the greater the proportion of acceleration in the SOC trajectory planning. Fig.5 shows a comparison of linearly decreasing SOC planning trajectory, velocity-based SOC planning trajectory, acceleration-based SOC planning trajectory and theoretically optimal SOC planning trajectory (which can be derived from the DP algorithm).

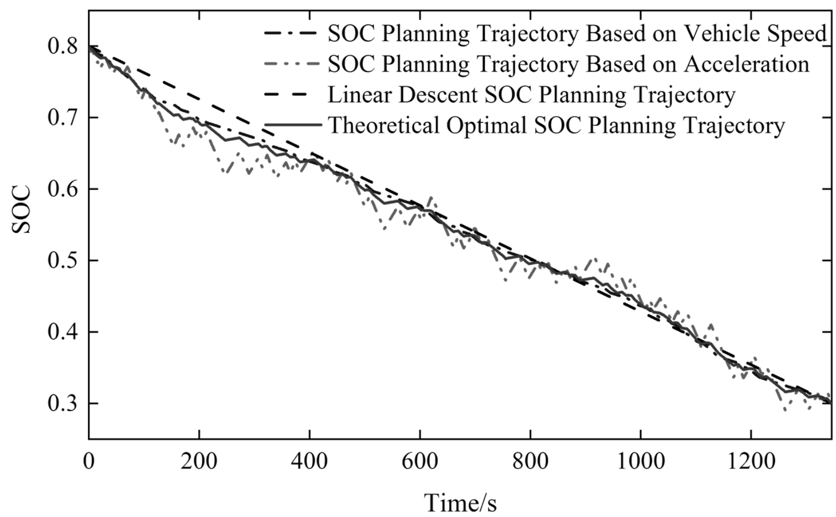

Fig.5 Comparison of different SOC planning trajectories

It can be seen from Fig.5 that the vehicle velocity based-SOC planning trajectory fluctuates less frequently, while the acceleration based-SOC planning trajectory fluctuates more frequently, and the theoretical optimal SOC planning trajectory is between the two. Since the power allocation factor s is in the range of [0, 1] and has only one degree of freedom, the optimal power distribution factor can be obtained by exhaustive enumeration or fitting method, so as to obtain the optimal battery SOC planning trajectory close to the theory [16].

4. SOC trajectory following strategy

The flow of the SOC planning based-energy management strategy is shown in Fig.6. The driver inputs the destination to the vehicle at the beginning of the travel, and the vehicle obtains traffic information such as historical speed from the ITS and the cloud. If the travel is short and can be reached by pure electric power, the energy management strategy will not be activated. If the power battery power is not enough to support the vehicle to reach the destination, the LSTM globalization in the spatial domain is performed. The vehicle speed is predicted, and the full SOC trajectory is planned. When the vehicle starts to move, the trajectory tracking strategy distributes the torque between the engine and the motor in real-time based on the required power and actual SOC feedback from the inverse vehicle model.

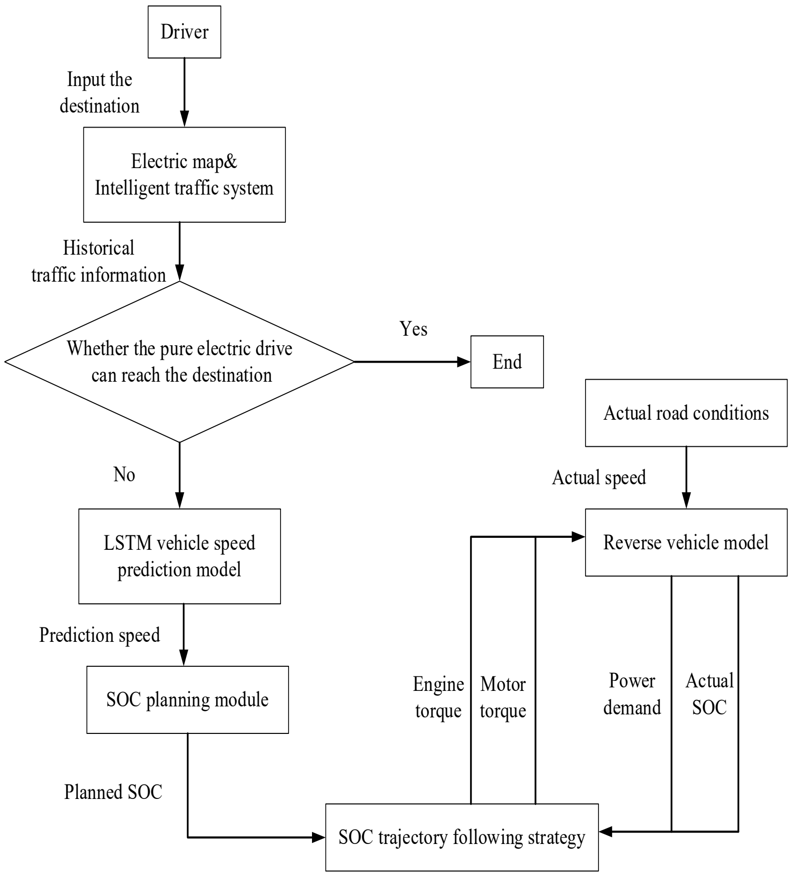

Fig.6 Energy management strategy flow

When the vehicle reaches the destination, the SOC trajectory tracking strategy constructed to drain the power battery to close to the pre-set value that contains 10 control rules, shown as Table 3.

Table 3

Logic threshold control rule based on traffic information fusion

Demand torque T_{req}	Battery state of charge SOC	Operating mode	Engine torque T_e	Motor torque T_m
$T_{req}<0$	$SOC<SOC_{\_ref\_h}$	Regenerative brake	$T_e=0$	$T_m=T_{req}$
$T_{req}<0$	$SOC>=SOC_{\_ref\_h}$	Mechanical brake	$T_e=0$	$T_m=0$
$T_{e\_max}>T_{req}>T_{e\_min}$	$T_{req}>T_{e\_max}$	Parallel drive	$T_e=T_{e\_max}$	$T_m=T_{req}-T_{e\_max}$
	$T_{req}>T_{m\_max}$	Parallel drive	$T_e=T_{req}-T_{m\_max}$	$T_m=T_{m\_max}$
	$SOC>SOC_{\_ref\_h}$	Pure motor drive	$T_e=0$	$T_m=T_{req}$
	$SOC_{\_ref\_l}>SOC$	Engine drive	$T_e=T_{req}$	$T_m=0$
$T_{e\_max}>T_{req}>T_{e\_opt}$	$SOC_{\_ref}>=SOC>=SOC_{\_ref\_l}$	Driving charging	$T_e=T_{e\_max}$	$T_m=T_{req}-T_{e\_max}$
	$SOC_{\_ref\_h}>=SOC>=SOC_{\_ref}$	Parallel drive	$T_e=T_{e\_opt}$	$T_m=T_{req}-T_{e\_opt}$
$T_{e\_opt}>T_{req}>T_{e\_min}$	$SOC_{\_ref}>=SOC>=SOC_{\_ref\_l}$	Driving charging	$T_e=T_{e\_opt}$	$T_m=T_{req}-T_{e\_opt}$
	$SOC_{\_ref\_h}>=SOC>=SOC_{\_ref}$	Parallel drive	$T_e=T_{e\_min}$	$T_m=T_{req}-T_{e\_min}$

In Table3, the subscript "e" refers to the engine, and the subscript "m" refers to the motor. The parameters involved in the SOC trajectory tracking strategy are shown in Table 4.

Table 4

SOC trajectory following strategy parameter settings

Parameters	Definitions
T_{req}	Demand torque
SOC	State of charge
T_e	Engine torque
T_m	Motor torque
$SOC_{\_ref\_h}$	Upper limit of planned SOC applicable interval
$SOC_{\_ref}$	Planned SOC trajectory
$SOC_{\_ref\_l}$	Lower limit of planned SOC applicable interval
T_{e_max}	Maximum torque of engine in high-efficiency zone
T_{e_opt}	Maximum engine efficiency torque
T_{e_min}	Minimum torque of engine in high-efficiency area

5. Comparative analysis of simulation results

The effectiveness of the SOC planning method was verified under 3x, 4x and 5x field driving cycles respectively. The battery SOC trajectories of the CD-CS energy management strategy, the SOC linearly decreasing based-energy management strategy and the SOC planning based-energy management strategy under the above three driving cycles are shown in Fig.7. The SOC trajectory of the CD-CS energy management strategy decreases rapidly in the CD phase, and the SOC briefly rises at some time points as the vehicle enters regenerative braking mode. At about 2400s, the battery SOC drops to near the set lower limit of 0.3, and the vehicle enters the CS phase. During the CS phase, the battery SOC remains near the lower limit until the end of the travel. For the SOC linearly decreasing based-energy management strategy and the SOC planning based-energy management strategy, through adjusting the operating states of the engine and motor in real-time, the SOC drops along the planning curve is maintained, and the battery charge is just close to the lower SOC limit at the end of the travel.

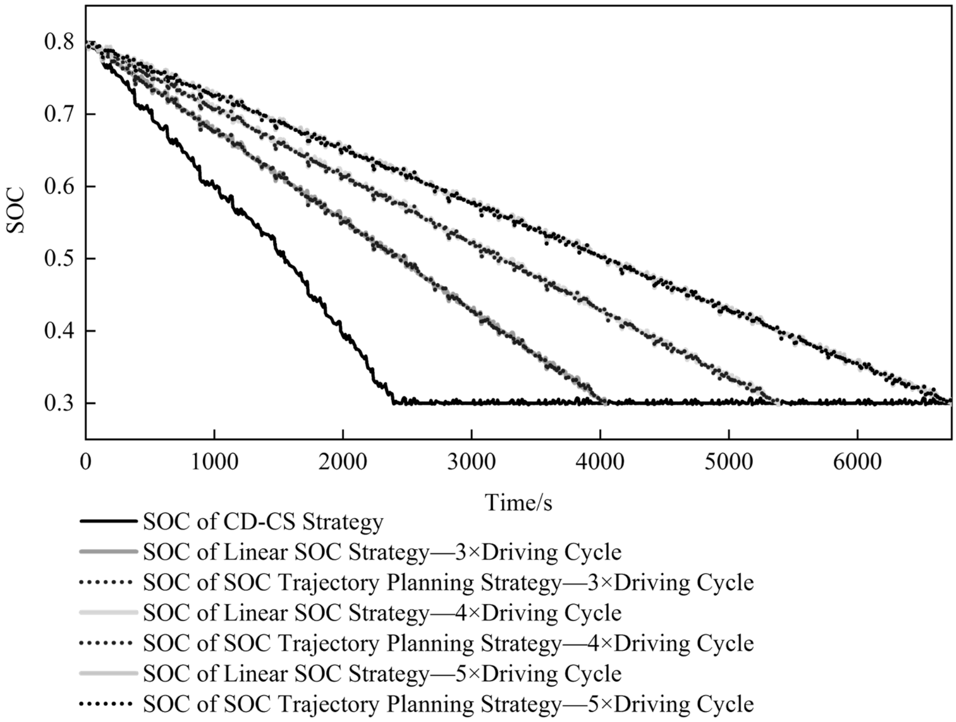

Fig.7 SOC Comparison of different strategies under different field driving cycles

The fuel consumption of the CD-CS energy management strategy, the SOC linearly decreasing based -energy management strategy and the SOC planning based-energy management strategy under 3x, 4x and 5x field driving cycles are shown in Table5. The SOC planning based-energy management strategy consumes the least fuel in the three strategies, regardless of the test drive cycle. Compared with the CD-CS energy management strategy, the fuel economy improvement range is 7.67% to 8.05%.Comparing with the SOC linear decreasing based-energy management strategy, the fuel economy improvement range is 7.93% to 8.99%.

Table 5

Fuel Consumption of different strategies under different field driving cycles

Test Driving cycle	Fuel Consumption/L		
	CD-CS Strategy	Linear SOC Strategy	Planning SOC Strategy
3×Filed Driving cycle	1.313	1.213	1.195
4×Filed Driving cycle	1.867	1.720	1.719
5×Filed Driving cycle	2.422	2.227	2.217

6. Conclusion

In this paper, taking the single-axle parallel hybrid vehicle as the research object and the roadside infrastructure as the carrier, the historical traffic information is obtained from the real-time traffic simulation model of LSTM global speed prediction. A SOC planning method based on the relationship between electrical energy consumption and the speed and acceleration per unit time is designed. The CD-CS energy management strategy, the SOC linearly decreasing based-energy management strategy and the SOC planning based-energy management strategy are simulated and compared under 3x, 4x and 5x field driving cycles, respectively. The results show that compared with the other two strategies, the SOC planning based-energy management strategy can improve the fuel economy by about 7.67% to 8.99%. In this paper, the SOC trajectory planning is carried out based on the global predicted vehicle speed with the trip as the unit. After the trip starts, the battery SOC planning trajectory is no longer dynamically adjusted. Subsequent research can integrate intelligent algorithms into SOC trajectory planning to realize the dynamic adjustment of the SOC planning trajectory during vehicle travel.

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