Paper ID APEN-MIT-2020_147
Applied Energy Symposium: MIT A+B
August 12-14, 2020 • Cambridge, USA

Research on Energy Management Strategy of Hybrid Electric Vehicles Based on Hierarchical Control in the Connected Environment

1st Shichun Yang
School of Transportation Science and engineering
Beihang University
Beijing, China
yangshichun@buaa.edu.cn

2nd Hehui Xie
School of Transportation Science and engineering
Beihang University
Beijing, China
hhui_xie@163.com

3rd Fei Chen*
School of Transportation Science and engineering
Beihang University
Beijing, China
johnfei1@126.com

4th Jian Liu
School of Transportation Science and engineering
Beihang University
Beijing, China
Liujian2049@yeah.net

5th Song Feng
School of Transportation Science and engineering
Beihang University
Beijing, China
fengsong@buaa.edu.cn

6th Junbing Zhang
School of Transportation Science and engineering
Beihang University
Beijing, China
zhangjunbing@buaa.edu.cn

Abstract—Vehicle energy management is the core technology of hybrid vehicles, which determines the fuel economy and emission performance of the vehicle. At present, most of the common energy management is based on known operating conditions, without considering actual road traffic information, which makes vehicles unable to achieve optimal energy management. With the development of GPS and ITS, future traffic information can be obtained in advance. In the paper, a hierarchical energy control method for hybrid electric vehicles is proposed. Model predictive control algorithm is utilized to predict the optimal vehicle velocity in the upper controller. The lower controller is designed to follow the optimal velocity, and uses the neural network control algorithm to optimize the power distribution between the engine and the motor to reduce fuel consumption. Compared with the traditional energy management strategy, the proposed method can prevent the vehicle from stopping at the red light, thereby reducing the fuel consumption of the vehicle to achieve the purpose of saving fuel consumption.

Keywords—Hierarchical Control, energy management, neural network, connected environment

I. Introduction

The growing environmental pollution and energy crisis have restricted the development of conventional Internal Combustion Vehicles. To meet these challenges, new energy vehicles have become the focus of research around the world due to their advantages of low energy consumption and low pollution [1,2]. Although pure electric vehicles have the characteristics of no pollution and zero fuel consumption, due to the limitations of current technology, such as small power battery capacity, short life, short driving range, etc., severely restrict the further development of pure electric vehicles. Therefore, hybrid vehicles that combine the advantages of pure electric vehicles and conventional vehicles have become the development trend of automobiles at this stage.

Energy management is the core technology of hybrid electric vehicles, and plays a vital role in fuel economy and emission performance of automobiles [3]. Vehicle energy management is related to many factors, such as vehicle velocity, road slope, and traffic information. Most of the current vehicle’s energy management is based on known operating conditions, without considering actual road traffic information, which prevents the vehicle from achieving optimal energy control [4]. In recent years, with the development of Intelligent Transportation System (ITS) and Global Positioning System (GPS), vehicles can communicate with vehicles (V2V), and can communicate with transportation facilities (V2I) [5]. All this information can help optimize vehicle energy management, thereby improving fuel economy performance [6].

Literature [7] puts forward an energy management strategy based on stochastic model predictive control, which makes use of vehicle position, driving direction and terrain information in this area to make hybrid electric vehicles drive in hilly areas with traffic congestion. Because the road information is known in advance, excellent energy management of the vehicle is realized. Literature [8] incorporated road terrain preview information into the energy management system of parallel hybrid electric vehicle, and studied the benefits of integrating future information (such as road slope) to the energy management of the whole vehicle. In the literature [9], model predictive control method is used to predict the traffic conditions, and the optimal control strategy is calculated within a certain prediction range, so as to avoid frequent braking at red light, so as to improve the fuel economy and realize the economical driving of the energy management system of hybrid electric vehicles. In reference [10], a hierarchical optimal controller for the velocity and power system of HEVs is constructed. At the vehicle level, velocity limit information and future road fluctuation information are used to optimize vehicle acceleration. At the power system level, the power distribution is determined by the future road slope and the optimal acceleration. The results show that the framework can better maximize fuel efficiency by optimizing power distribution and vehicle acceleration. Literature [11] proposed a stochastic dynamic programming (SDP) energy management method based on traffic information for commuter cars. This method not only meets the battery charge maintenance constraints and overall requirements, but also minimizes the average equivalent fuel consumption to the driving performance requirements of the vehicle power. Literature [12] proposed an energy management method for plug-in hybrid electric vehicles, whose driving cycle is predicted by GPS/GIS traffic information on uphill roads, thereby improving vehicle fuel economy.

In view of the above problems, the hierarchical energy management structure to improve the vehicle energy optimization is studied in the paper. The hierarchical management structure is composed of two controllers, where the upper controller predicts the vehicle optimal target velocity using model predictive control algorithm with the traffic information, the lower controller uses the control algorithm based on the neural network to allocate the required power of the vehicle between the engine and the motor according to the predicted velocity obtained by the upper controller, so as to achieve the purpose of improving fuel economy.

II. VEHICLE MODELING

The vehicle model used in the study is a typical parallel hybrid electric vehicle, whose structure is shown in Figure 1. The model will be built in MATLAB/Simulink, whose mathematical principles are not described in detail here.

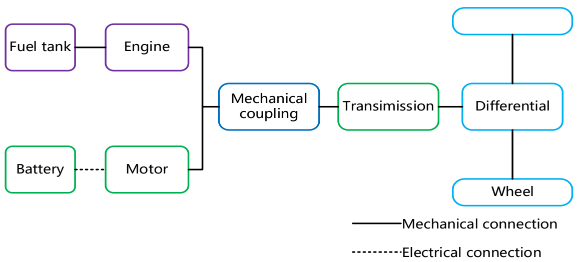

Fig1. Structure of parallel hybrid electric vehicle

III. THE CONTROLLER DESIGN

The designed vehicle energy management method is a hierarchical controller, whose specific structure is shown in Figure 2.

The upper controller uses the traffic information obtained by V2V and V2I to solve the optimal target vehicle velocity based on the traffic signal phase and timing model and model predictive control algorithm (MPC) to avoid the hybrid electric vehicle stopping at red light. The lower controller adopts the energy management optimization algorithm based on neural network control, and takes advantage of the target velocity information obtained by the upper controller to calculate the optimal torque distribution of power components, so as to reasonably distribute the vehicle's required power between the engine and the motor.

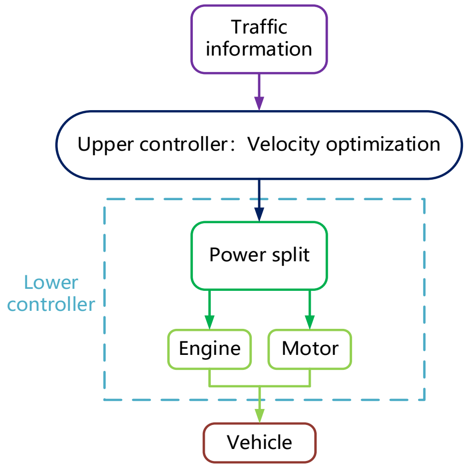

Fig2. Hierarchical energy management structure

A. Velocity Optimization for Eco-driving

The dynamic model of hybrid electric vehicle is as follows:

$$\begin{cases} \dot{x}(t) = f\big(x(t), u(t)\big) = -fg - \frac{1}{2m} C_D A \rho v(t)^2 - g\alpha + a(t) \\ x(t) = [s(t) \quad v(t)]^T \end{cases} \tag{1}$$

Among which, s, v, a, m are the position, velocity, acceleration and mass of the vehicle respectively; C_D is wind resistance coefficient; ρ is air density; A is frontal area; f is rolling resistance coefficient; α is the road slope.

In the paper, the traffic signal timing model is applied to solve the target velocity range for the sake of avoiding the vehicle stopping at red light. The calculation principle diagram of the target velocity range is shown in Figure 3 [13].

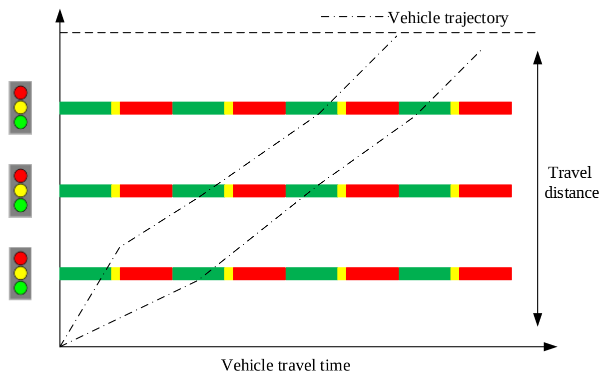

Fig3. Schematic diagram of velocity range calculation principle

When the next intersection is a green light and meets the constraint of the maximum driving velocity, the vehicle can accelerate to the maximum possible value that is not allowed to exceed the maximum allowable speed, so as to ensure that it passes through the intersection before the arrival of the red light (at this time, it is the upper speed limit); or slow down to ensure that passing through the intersection just changes from red light to the next green light (at this time, it is the lower speed limit). When the next intersection is a red light, the vehicle must slow down to ensure that passing through the intersection just changes from red light to green light (at this time, it is the upper speed limit); or slow down to pass the intersection before the end of the next green light (at this time, it is the lower speed limit). Based on this principle, the upper and lower limits of the vehicle target speed range are as follows [14]:

$$v_h(t)=\begin{cases}\frac{d_a(t)}{K_w t_c-t_g-t} & red\ light\\ v_{max} & green\ light\ \&\ \frac{d_a(t)}{K_w t_c-t}\le v_{imax}\\ \frac{d_a(t)}{K_w t_c+t_r+t_y-t} & other\ case\ at\ green\ light\end{cases} \quad (2)$$

$$v_l(t)=\begin{cases}\frac{d_a(t)}{K_w t_c-t} & red\ light\\ \frac{d_a(t)}{K_w t_c-t} & green\ light\ \&\ \frac{d_a(t)}{K_w t_c-t}\le v_{imax}\\ \frac{d_a(t)}{(K_w+1)t_c-t} & other\ case\ at\ green\ light\end{cases} \quad (3)$$

$$v_l(t)\le v_{target}(t)\le v_h(t) \quad (4)$$

$$t_c=t_g+t_r+t_y \quad (5)$$

Where, v_{target} is the vehicle target velocity, v_l and v_h are the upper and lower limits of the ideal vehicle velocity respectively. $d_a(t)$ is the distance between the vehicle's position s and the traffic signal light a, K_w is the cycle number of traffic signal lights, which is an integer; t_r、$t_g$and t_y are the durations of red light, green light and yellow light respectively. t_c is the time of a traffic signal light cycle; t is the driving time; v_{max} is the maximum velocity of the vehicle.

In the paper, the model predictive control algorithm is used to solve the optimal target velocity of vehicles, whose specific expression is as follows:

$$min\,J=\sum_{t=k}^{k+T-1}\omega_1\frac{\dot{m}_f(t)\delta(t)}{s(t+T-1)-s(t)}+\omega_2\left[v(t)-v_{target}(t)\right]^2+\omega_3 a(t)^2 \quad (6)$$

$$v_{min}\le v(t)\le v_{max} \quad (7)$$

$$a_{min}\le a(t)\le a_{max} \quad (8)$$

Among which, $\omega_i(i=1,2,3)$is a weight coefficient, $\dot{m}_f$ is the equivalent fuel consumption rate of vehicle, v_{target} is the vehicle target velocity, and T is a model prediction time length, v is vehicle driving velocity, a is vehicle acceleration (control variable), $t=k$ represents the time k, v is minimum vehicle velocity, v_{max} is maximum vehicle velocity, a_{min} is minimum acceleration, v_{max} is maximum acceleration.

The first item of the objective function optimizes the fuel consumption per unit mileage, that is, optimizes the fuel economy; The second optimization is the difference between the driving velocity and the target velocity obtained based on traffic information, that is, the optimized velocity is as close as possible to the ideal target velocity, thus reducing the vehicle stopping in front of the red light; The last optimization is the longitudinal acceleration of the vehicle. The goal is to reduce the times of acceleration and deceleration and the absolute value of acceleration, so as to improve fuel economy. The optimized variables output by this formula are the optimal target velocity v_{target} and position s of the hybrid electric vehicle at the current moment.

To solve the objective function of model predictive control shown in formula (6), it is necessary to transform formula (1) into a state space model, as shown in the following formula (9):

$$\begin{cases}\dot{x}(t)=f\big(x(t),a(t)\big)\\ f\big(x(t),a(t)\big)=\begin{bmatrix}v(t)\\ -fg-\frac{1}{2m}C_D A\rho v(t)^2-g\alpha+a(t)\end{bmatrix}\\ x(t)=[s(t)\quad v(t)]^T\end{cases} \quad (9)$$

Then, the formula (9) is transformed into the discrete state space model form formula (10):

$$\begin{cases}x(k+1)=Ax(k)+Ba(k)\\ Ax(k)=\begin{bmatrix}v(t)\\ -fg-\frac{1}{2m}C_D A\rho v(t)^2-g\alpha\end{bmatrix}\\ B=[0\quad 1]^T\end{cases} \quad (10)$$

The MPC objective function described in formula (6) is rewritten into the quadratic programming form shown in formula (11):

$$\begin{cases}min\left[\frac{1}{2}\left(y_i-y_{iobj}\right)^T Q_i\left(y_i-y_{iobj}\right)\right]\\ P_i y_i\le q_i\\ C_i y_i=b_i\\ y_i=[u_i(t),x_i(t+1),\cdots u_i(t+T-1),x_i(t+T)]^T\end{cases} \quad (11)$$

Among which, y_i and y_{iobj} are state variables and corresponding target values in the form of quadratic programming; Q_i is diagonal matrix; P_i,q_i,C_i and b_i are all matrices related to state variables.

B. Power Split Under the Optimal Velocity

The lower controller designed in the paper is an energy management optimization algorithm. After the upper controller obtains the optimal vehicle target velocity, the lower controller performs optimal torque distribution. On the one hand, it follows the optimal target velocity obtained by the upper controller, on the other hand, it realizes the optimal distribution of vehicle power demand between the engine and the motor.

The energy management optimization problem of hybrid electric vehicle is a typical nonlinear, multivariable and multi-constrained problem. Excellent control cannot be achieved by conventional control methods. Because artificial neural network is a mathematical model to simulate the thinking mode of human brain and an important way to simulate human intelligence, which reflects some basic characteristics of human brain function. Neural network control is an intelligent control method developed by combining neural network with control theory, consequently neural network control for energy management is chosen in the paper.

In order to realize the optimal torque distribution of hybrid electric vehicle, neural network control method is applied to optimize the energy management in the paper. In the neural network, the input nodes of the neural network are used to represent the input signals, i.e. the required torque T_{req} and the battery SOC, and the output nodes are used to represent the output signals, i.e. the engine torque T_e.

Figure 4 shows the structure of neural network, which is composed of input layer, hidden layer and output layer.

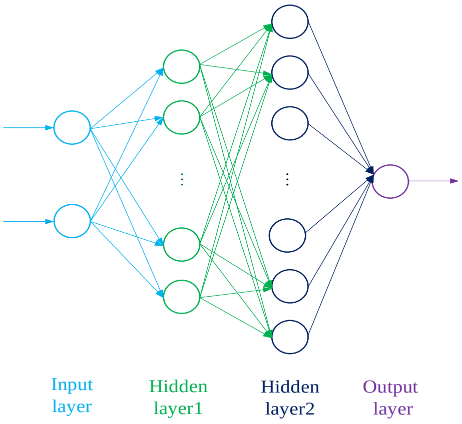

Fig4. Vehicle velocity optimization on the upper controller

The system is composed of two kinds of networks, namely forward network and backward network, in which the forward network calculates the current loss in turn from front to back, and the backward network updates the system parameters from back to front by gradient descent method.

1) Forward Network

The first layer of the network is the input layer, whose node distribution corresponds to the input variable $x_i(T_{req}$、 SOC$)$, so that the input vector is transmitted to the second layer, and the output of each node i in the layer can be expressed as formula (12):

$$f_1(i) = x_i \tag{12}$$

The second layer of the network is hidden layer, The input of hidden neurons is the weighted sum of all inputs, namely

$$x_j = \sum_i \omega_{ij} x_i \tag{13}$$

Among which, ω_{ij} is the weight between the input layer and the hidden layer.

The output x_j' of hidden layer neurons applies sigmoid function to excite x_j as following formula (14):

$$x_j' = f(x_j) = \frac{1}{1+e^{-x_j}} \tag{14}$$

Derive the output x_j' of hidden neurons as formula (15):

$$\frac{\partial x_j'}{\partial x_j} = x_j'(1 - x_j') \tag{15}$$

After solving the similar multi-layer hidden layer, the output of neurons in the output layer can be obtained as follows:

$$y_m(k) = \sum_j \omega_{jo} x_j' \tag{16}$$

Among which, ω_{jo} is the weight between the hidden layer and the output layer.

2) Backward Network

After constructing the neural network, it is necessary to constantly update the weight coefficient w_{ij} between the input layer and the hidden layer and weight coefficient w_{jo} between the hidden layer and the output layer by gradient descent method. The following is the specific update method:

Assuming that the expected output of the network is y and the actual output is y_m, the approximation error of the network is as following formula (17):

$$e(k) = y(k) - y_m(k) \tag{17}$$

The gradient descent method is used to modify the adjustable parameters, and the following objective function (18) is defined:

$$E = \frac{1}{2}\sum_{i=1}^{r} e(k)^2 \tag{18}$$

The δ learning algorithm is applied to adjust the weights of each layer. The weight of the output layer is adjusted by formula (19):

$$\Delta w_{jo}(k) = -\eta \frac{\partial E}{\partial w_{jo}} = \eta e(k) x_j' \tag{19}$$

Among which, η is the learning rate, $\eta \in (0,1)$。

At time $k+1$, the weights of the neural network are as follows:

$$w_{jo}(k+1) = w_{jo}(k) + \Delta w_{jo} \tag{20}$$

The learning algorithm of connection weight w_{ij} between hidden layer and input layer is as follows:

$$\Delta w_{ij}(k) = -\eta \frac{\partial E}{\partial w_{ij}} = \eta e(k) \frac{\partial y_m}{\partial w_{ij}} \tag{21}$$

Among which,

$$\frac{\partial y_m}{\partial w_{ij}} = \frac{\partial y_m}{\partial x_j'} \frac{\partial x_j'}{\partial x_j} \frac{\partial x_j}{\partial w_{ij}} = w_{jo} \frac{\partial x_j'}{\partial x_j} x_i = w_{jo} x_j'(1 - x_j') x_i$$

At time $k+1$, the weights of the neural network are as follows:

$$w_{ij}(k+1) = w_{ij}(k) + \Delta w_{ij} \tag{22}$$

To avoid oscillation and slow convergence in the process of weight learning, it is necessary to consider the influence of the last weight change on the current weight change, that is, to add momentum factor α. The adjusted weight learning algorithm of the output layer is formula (23):

$$w_{jo}(k+1) = w_{jo}(k) + \Delta w_{jo} + \alpha\left(w_{jo}(k) - w_{jo}(k-1)\right)$$
$$w_{ij}(k+1) = w_{ij}(k) + \Delta w_{ij} + \alpha\left(w_{ij}(k) - w_{ij}(k-1)\right)$$

(23)

Among which, α is momentum factor , $\alpha \in (0,1)$

IV. Simulation Results and Analysis

A. Simulation Parameter Setting

In the upper controller, the initial velocity of the vehicle is set to 0, the maximum and the minimum velocity are respectively 20m/s and 0m/s, and the target driving distance is 6000m; The number of traffic signal lights is set to 11, with the duration of red, green and yellow lights being 18s, 20s and 2s respectively, and the intervals of traffic signal lights being 450m, 500m, 300m, 500m, 700m, 500m, 600m and 1000m; Set the simulation iteration step size to 0.05s; Set the initial value of battery's SOC to 0.7; The parameters for hybrid electric vehicles are shown in Table I below.

TABLE I. PARAMETERS OF VEHICLE'S MAIN COMPONENTS

The main components	parameter name	parameter
engine	maximum power	41KW
motor	maximum power	75KW
battery	capacity	16AH
vehicle	vehicle mass	1350kg
	frontal area	$2m^2$
	radius of vehicle	0.343m
	rolling resistance coefficient	0.018
	final reduction drive gear ratio	4.8
	wind resistance coefficient	0.335
	air density	$1.2kg/m^3$

In order to intuitively understand the advantages and disadvantages of the proposed neural network energy management optimization method, rule-based energy management strategy of hybrid electric vehicle, which has been widely used at present, is selected to compare in the paper, so as to analyzes its performance.

B. Simulation Results

The black curve in Figure 5 is the trajectory of the hybrid electric vehicle. In the figure, the green solid line represents the green light time window, the yellow solid line represents the yellow light time window and the red solid line represents the red light time window. It can be seen from the figure that there is no intersection between the vehicle trajectory and the red、yellow solid lines, which indicates that the vehicle did not encounter red lights when passing all traffic lights, and the slope of the trajectory is not equal to zero. Therefore, the target velocity prediction model based on the information of road traffic lights can effectively avoid the hybrid electric vehicles stopping at red lights.

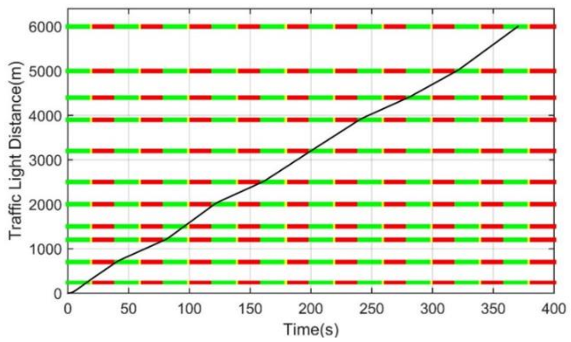

Fig5. Trajectory of hybrid electric vehicle

Figure 6 is the predicted vehicle velocity graph of hybrid electric vehicle based on road traffic signal information and MPC. It can be seen from the figure that the velocity of vehicles does not remain constant, but rises and falls, which is a reasonable change brought by the vehicle to avoid stopping at the red light of the traffic signal light. The application of model predictive control is to ensure that the vehicle velocity changes smoothly with the variation of traffic, without drastic changes, so as to achieve the purpose of saving fuel.

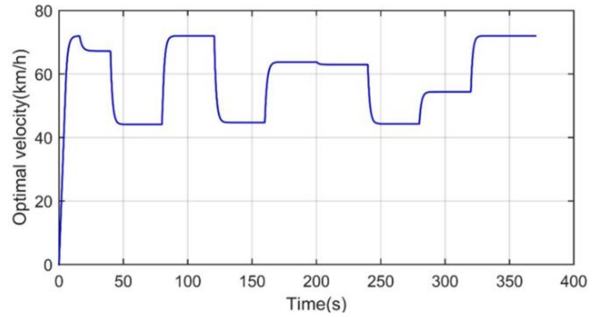

Fig6. Prediction of vehicle velocity based on SPAT and MPC

Figure 7 shows the SOC trajectory of power battery when the lower controller of hybrid electric vehicle is controlled based on rules and neural network. It can be seen from the figure that the initial values of SOC of power battery are all around 0.7. From the range of SOC fluctuation, the SOC of battery based on neural network control adopted in this paper drops more obviously. This is because the vehicle velocity is constantly changing, and it is more economical to drive with motor frequently than with engine.

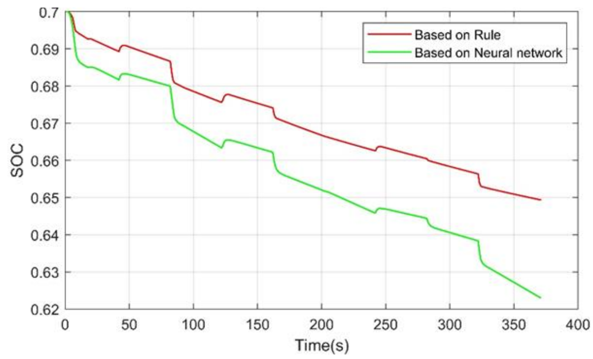

Fig7. SOC change curve of power battery

Figure 8 is the exhaust emission variation curve of the lower controller based on rules and neural network. It can be seen from the figure that the emission of HC, CO and NOx corresponding to the lower control method based on neural network is lower than the emission of exhaust gas under the rule-based control.

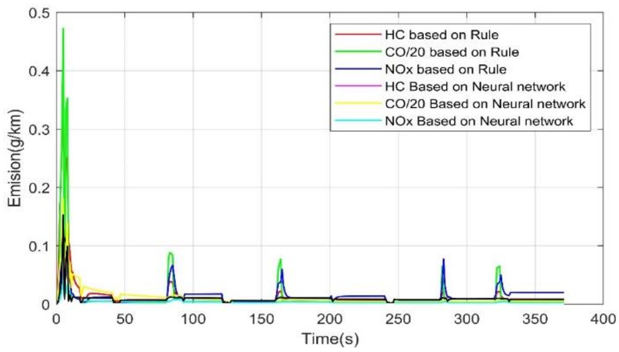

Fig8. Emission based on neural network and rules

Table2 compares a series of simulation results of vehicles based on neural network and rules. On the one hand, it can be seen from the table that HC, CO and NOx emissions of vehicles are 0.498g/km, 2.664g/km, 0.283g/km and 0.557g/km, 7.879g/km and 0.286g/km under neural network and rule-based control, respectively. Compared with the rule-based control method, the HC, CO, and NOx emission performance based on the neural network are increased by 10.56%, 66.19% and 1.05%, respectively. Therefore, the energy management control method based on neural network has achieved excellent emission performance of hybrid electric vehicles.

On the other hand, it can be seen from the table II that for hybrid electric vehicles, the fuel consumption per 100 km corresponding to the lower control method based on neural network is lower than that based on rules. The average fuel consumption per 100 kilometers of vehicles is 2.8L/100km and 4.3L/100km under neural network and rule-based control, respectively. Compared with the rule-based control method, the fuel economy under neural network is improved by 34.88%. Therefore, the energy management control method based on neural network improves the fuel economy of hybrid electric vehicles.

TABLE II. COMPARISION OF SIMULATION RESULTS

item	control strategy	
	Based on rule	Based on neural network
CO (g/km)	7.879	2.391
HC (g/km)	0.557	0.492
NO_x (g/km)	0.286	0.243
FC (L/100km)	4.3	3.4
End SOC	0.6493	0.6230
motor driving efficiency	0.59	0.72
vehicle system efficiency	0.147	0.164

From the analysis of the above simulation results, it can be seen that for the upper controller, on account of that the hybrid electric vehicle can obtain the road traffic information in advance in the connected environment, the vehicle can effectively avoid stopping at the red light when passing through the traffic lights. In addition, the velocity and required power of the vehicle can be predicted in advance, so that the required power can be distributed between the engine and the motor more reasonably, and the fuel economy can be improved. As for the lower controller, on the premise of satisfying the dynamic performance of HEV, the neural network control strategy can realize the rational distribution of energy between engine and motor, and improve the efficiency of motor and vehicle control system. More importantly, it not only improves the fuel economy of the vehicle, but also reduces the emissions of CO, HC and NOx.

V. CONCLUSION

In this paper, the energy management optimization of hybrid electric vehicles in connected environment is studied, where a hierarchical controller is designed.

The upper controller makes use of the traffic information obtained by V2I to solve the optimal target velocity of hybrid vehicles based on the traffic signal timing model and model predictive control algorithm. The vehicle does not encounter the red light when passing through the traffic signal, which effectively avoids the situation of vehicles stopping at the red light, thus reducing fuel consumption.

The lower controller adopts the energy management optimization algorithm based on neural network control. Using the target velocity information obtained by the upper controller, on the one hand, it can achieve vehicle velocity following; on the other hand, it can achieve torque distribution of various power components, effectively avoiding frequent engine start and stop, thus realizing reasonable distribution of vehicle power demand between engine and motor. Compared with the rule-based control method, the average fuel economy of the vehicle is improved by 34.88%, and the emission performance of HC, CO and NOx is improved by 10.56%, 66.19% and 1.05% respectively under the neural network control, thus achieving excellent fuel economy and emission performance of the hybrid electric vehicle.

ACKNOWLEDGMENT

This work is supported by National Key R&D Program of China (Grant No. 2017YFB0103400).

REFERENCES

[1] Zhang, Fengqi, et al. "Energy management strategies of connected HEVs and PHEVs: Recent progress and outlook." Progress in Energy and Combustion Science 73.JUL.(2019):235-256.

[2] Chen, Z.; Xiong, R.; Wang, K.; Jiao, B. Optimal Energy Management Strategy of a Plug-in Hybrid Electric Vehicle Based on a Particle Swarm Optimization Algorithm. Energies 2015, 8, 3661-3678.

[3] Wang, X.; He, H.; Sun, F.; Zhang, J. Application Study on the Dynamic Programming Algorithm for Energy Management of Plug-in Hybrid Electric Vehicles. Energies 2015, 8, 3225-3244.

[4] Chunhua, Zheng, Guoqing, et al. "An energy management approach of hybrid vehicles using traffic preview information for energy saving." Energy Conversion and Management (2015).

[5] Qiu, Lihong, et al. "Global optimal energy management control strategies for connected four-wheel-drive hybrid electric vehicles." Iet Intelligent Transport Systems 11.5(2017):264-272.

[6] Guo, Lulu , et al. "Optimal Energy Management for HEVs in Eco-Driving Applications Using Bi-Level MPC." IEEE Transactions on Intelligent Transportation Systems 18.8(2017):2153-2162.

[7] Zeng, Xiangrui , and J. Wang . "A Parallel Hybrid Electric Vehicle Energy Management Strategy Using Stochastic Model Predictive Control With Road Grade Preview." IEEE Transactions on Control Systems Technology 23.6(2015):2416-2423.

[8] Zhang, Chen , et al. "Role of Terrain Preview in Energy Management of Hybrid Electric Vehicles." IEEE Transactions on Vehicular Technology 59.3(2010):1139-1147.

[9] Yu K, Yang J, Yamaguchi D. "Model predictive control for hybrid vehicle ecological driving using traffic signal and road slope information. " Control Theory Technol 2015;13(1):17–28.

[10] Hu, Jia, et al. "Integrated optimal eco-driving on rolling terrain for hybrid electric vehicle with vehicle-infrastructure communication." Transportation Research Part C: Emerging Technologies (2016): 2016;68:228–44.

[11] Jiao, X.; Shen, T. SDP Policy Iteration-Based Energy Management Strategy Using Traffic Information for Commuter Hybrid Electric Vehicles. Energies 2014, 7, 4648-4675.

[12] Liu Y, Li J, Ye M, Qin D, Zhang Y, Lei Z. Optimal energy management strategy for a plug-in hybrid electric vehicle based on road grade information. Energies 2017;10(4):412.

[13] Asadi, Behrang , and A. Vahidi . "Predictive Cruise Control: Utilizing Upcoming Traffic Signal Information for Improving Fuel Economy and Reducing Trip Time." IEEE Transactions on Control Systems Technology 19.3(2011):707-714.

[14] Qian L J, Qiu L H, Si Y, et al. Global energy management optimization for a group of 4WD hybrid electric vehicles in connected vehicle environment (in Chinese). Sci Sin Tech, 2017, 47: 383–393, doi: 10.1360/N092016-00202.