ORIGINAL ARTICLE

Neural Network Energy Management Strategy for Series Hybrid Electric Car

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Abstract: A design concept of energy management and control strategy for hybrid electric car based on neural network and global optimization is proposed. The control strategy can effectively combine the advantages of global optimization algorithm and neural network algorithm. The minimum fuel consumption of the engine model can be derived. Simulation and analysis of the known road cycle conditions were carried out. The simulation platform ADVISOR2002 is used for the secondary development. The control strategy, the power monitoring control strategy and the thermostat control strategy were simulated and compared. The strategy has a strong adaptive capacity which can further improve the fuel economy of hybrid car.

Keywords：hybrid car; energy management; neural network; global optimization; power monitoring; thermostat

Introduction

Energy management strategy is the core of hybrid cars. At present, the series hybrid electric car control strategy mainly includes the power monitoring control strategy, the thermostat control strategy and others. The power monitoring control strategy accounts for the majority due to its real-time performance and simple control parameters. It can overcome the shortcomings of many other control strategies. However, the cost is very high, lack of self-learning and adaptive abilities. Studies proved that the neural network has a better self-learning ability and is an effective method for optimization.

In this study, an energy management and control strategy based on neural network and global optimization is proposed for a series hybrid car. The least fuel consumption route is obtained to maintain the optimal route to travel based on the self-learning ability of neural network algorithm[2]. After optimization, the engine model can be obtained according to the minimum fuel consumption route, which can provide data for further optimization of engine performance in the future. Based on the simulation analysis of the known road cycle conditions, the fuel consumption under the energy management control strategy can be obtained and verified by the simulation test of ADVISOR2002. Simulation results showed that the optimized energy management strategy is better than common energy management and control strategy, which can further reduce the fuel consumption.

1. Establishment of car model

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is properly cited.

The research object is a series hybrid car. Table 1 shows the vehicle and powertrain main parameters. The symbols in the figure are: speed ω (rad/s), torque T (N·m), efficiency ŋ, transmission ratio i and auxiliary power unit (APU).

Table 1 Vehicle and powertrain main parameters

Parameter value		Parameter value	
Engine maximum power	43 kW	Transmission	Manual (5 Gear)
Engine displacement volume, V	1.5 L	Rolling radius, r	0.282 m
Maximum motor power	58 kW	Dray coefficient, C_D	0. 335
Battery rated capacity, C_N	12 Ah	Vehicle upwind area, A	2.0 m^2
Total mass of vehicle	1267 kg	Rolling resistance coefficient, f	0.009

From Figure 1, the power relationship between the APU and the battery is:

$$P_{mot} = P_{APU} + P_{ess} \qquad (1)$$

$$P_{mot} = \omega(t) \cdot T_w(t) = P_m \qquad (2)$$

where P_{mot} —— Pavement demand power, kW;

P_{APU} —— Auxiliary power unit (APU) output power, kW;

P_{ess} —— Battery power, kW;

ω(t) —— Wheel speed, rad/s;

P_m —— Motor Power, kW;

The relationship between the speed of the motor and the wheel is:

$$n_w(t) = \frac{n_m(t)}{i_{gb}(k) i_r \rho} \qquad (3)$$

where $i_{gb}(k)$ —— Transmission kth gear ratio;

$n_w(t)$ —— Wheel speed, r/min;

$n_m(t)$ —— Motor speed, r/min;

ρ —— Torque coupling ratio;

k —— Gear (1–5)

For the known cycle conditions, a certain wheel speed (n_w) and torque (T_w) can be derived [3]:

$$n_w(t) = \frac{v(t)}{0.377r} \qquad (4)$$

$$T_w(t) = [mgf + mgi + \frac{C_D A v^2(t)}{21.15} + \delta m \frac{dv(t)}{dt}]r \qquad (5)$$

where v(t) —— Cycle speed t time, km/h;

m —— Car mass, kg;

g —— Gravitational acceleration, m/s^2;

I —— Road gradient;

δ —— Mass conversion factor;

r —— Tyre rolling radius, m

2. Design of Energy Management Control Strategy for Hybrid Electric Car

2.1 Application of Dynamic Programming Algorithm

Under the known road cycle conditions, the driving cycle is divided into N stages by discretization, and the time step of each stage is Δt (1 s). Under certain constraints, the dynamic programming method is applied from the last stage to the end of the first stage, and the optimal solution of each stage is calculated. Finally, the optimal control of the whole cycle condition is obtained.

2.1.1 Objective function

In order to reduce the fuel consumption and improve the fuel economy, the optimal control problem of the powertrain is equivalent to the problem of minimizing the fuel consumption B_H (kg). The mathematical model of the minimum fuel consumption is:

$$\min J = Cost_{fuel} \cdot \sum_{t=0}^{N-1} B_H(t) \qquad (6)$$

among them,

$$B_H = \int_0^t b_e(t) P_e(t) dt \qquad (7)$$

As this study discusses the series hybrid electric car, the car drive is basically relied on the energy consumption of fuel. The battery is the only auxiliary power source. At the same time, it meets ΔSOC=0

where $Cost_{fuel}$—— Current fuel price;

B_H——t Time system fuel consumption, kg;

P_e—— Engine power, kW;

$b_e(t)$—— Engine fuel consumption ratio, kg/kWh

2.1.2 Constraints

The variables in the powertrain system state are $i_{gb}(k)$ and SOC, the control variables are engine torque (T_e) and gear (k).

The inequality constraints for state variables and control variables are:

$$\begin{cases} SOC_{min} \le SOC \le SOC_{max} \\ \omega_{e\,min} \le \omega_e \le \omega_{e\,max} \\ T_{e\,min} \le T_e \le T_{e\,max} \\ \omega_{m\,min} \le \omega_m \le \omega_{m\,max} \\ T_{m\,min} \le T_m \le T_{m\,max} \end{cases} \qquad (8)$$

where T_{mmin} and T_{mmax}—— minimum and maximim Torque output at the current speed of the motor, N/m;

ω_{mmin} and ω_{mmax}—— minimum and maximim motor speed, r/min;

T_{emax} and T_{emin}—— minimum and maximim Torque output at the engine's current speed, N/m;

ω_{emax} and ω_{emin}—— minimum and maximim engine speed, r/min

Equations (1) and (4) are the equality constraints of state variables and control variables。

In addition, the constraints also include the motor maximum power, voltage, current, battery maximum charge and discharge current.

2.1.3 Dynamic programming solution

Using dynamic programming to solve the inverse calculation, the calculations are as follows:

(1) From t = N, at a certain time, t (t = 0, 1, L, N-1), select all the values k, calculate the optimal solution of the time, calculate $\min J_{t,k}$ using (SQP) algorithm, SQP algorithm has a good global convergence and local superlinear convergence, which is an effective method to solve the nonlinear programming problem[4].

(2) Time t minus 1 s，repeat step (1).

In this way, the optimal control variable for each moment can be obtained.

2.2 Parameter Optimization of Global Optimization Energy Management Control Strategy Based on Neural Network

Based on the global optimization of the optimal fuel consumption route, the neural network algorithm is used to simulate the optimal energy consumption route by using the self-learning ability so that the vehicle can follow the route. Common neural network models are feedforward neural network, feedback neural network and self-organizing network (SOM). The self-organizing feature mapping network has the characteristics of topology maintenance and vector quantization. It is a kind of no mentor learning network. It changes the network parameters and structure by automatically searching the inherent laws and essential attributes of the samples. Figure 2 shows that SOM is a two-layer neural network, including the input layer and the competitive layer (output layer).

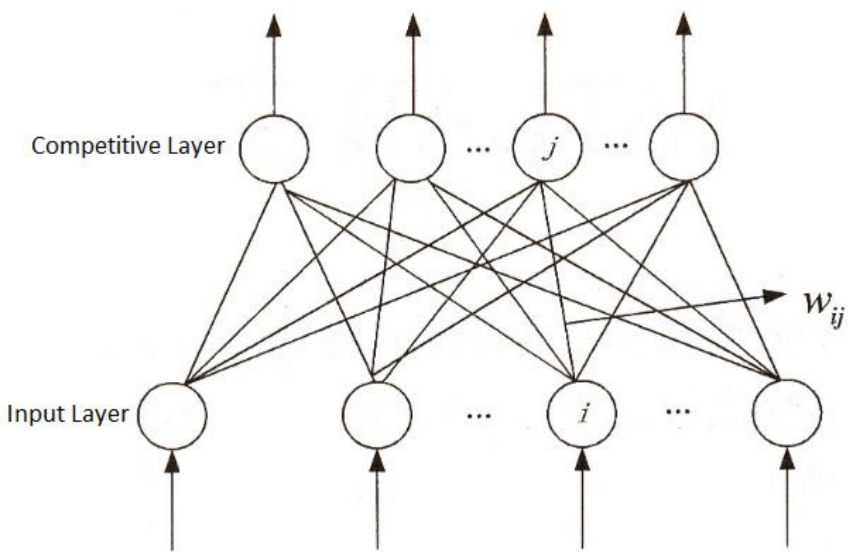


Figure 2 Basic structure of the self-organizing network

Set the input mode of the network to $P_k = \left(p_1{}^k, p_2{}^k, L, p_n{}^k\right) \quad k = 1,2,L,q$, where k represents the first input pattern; n is the dimension of the input vector; w_{ij} is the weight of the input layer; i is the i-th input variable; and j is the j-th subset of the input variable. The vector of the connection between the neuron j and the input neuron is $W_{ji} = \left(w_{j1}, w_{j2}, L, w_{jn}\right), \quad i = 1,2,L,n \quad j = 1,2,L,M$; where M is the number of neurons distributed by the output layer. The analytical solution is as follows:

Step 1 Assign the network connection right {w_{ij}} to the random value within the interval [0,1] to determine that the initial value of the learning rate ŋ (t), where ŋ (0) (0 <ŋ (0) <1). Confirm the initial value of $N_g(t)$ as $N_g(0)$ and the total number of learning.

Step 2 An optional mode P_k in the learning mode q is provided to the input layer of the network and normalized:

$$\overline{P}_k = \frac{P_k}{\|P_k\|} = \frac{(p_1{}^k, p_2{}^k, L, p_n{}^k)}{[(p_1{}^k)^2 + (p_2{}^k)^2 + L + (p_n{}^k)^2]^{1/2}} \quad (9)$$

Step 3 The connection weight vector, $W_j=(w_{j1},w_{j2},L,w_{jn})$ is normalized to calculate the Euclidean distance between Wj and Pk：

$$\overline{W_j} = \frac{W_j}{\|W_j\|} = \frac{(w_{j1}, w_{j2}, L, w_{jn})}{[(w_{j1})^2 + (w_{j2})^2 + L + (w_{jn})^2]^{1/2}} \quad (10)$$

$$d_j = [\sum_{i=1}^{n} (\overline{p_i{}^k} - \overline{w_{ji}})^2]^{1/2}, \quad j=1,2,L,M \quad (11)$$

Step 4 Find the minimym distance (d_c) and determine the winning neurons (c)

$$d_c = \min_j [d_j], \quad j = 1,2,L,M \quad (12)$$

Step 5 The connection right is adjusted to correct the connection between all the neurons and the input neurons in the $N_g(t)$ of the competition layer：

$$\overline{w_{ji}(t+1)} = \overline{w_{ji}(t)} + \eta(t) \cdot [\overline{p_i{}^k} - \overline{w_{ji}(t)}]$$

$$j \in N_g(t), \quad j=1,2,L,M \quad (13)$$

Step 6 Select another learning mode to provide input to the network and return to step 3.

Step 7 Update the learning rate, ŋ(t) and $N_g(t)$, where t is the number of learning and T is the total number of learning.

Step 8 Let t = t+1, return to step 2 until t = T.

Step 9 Compare the winning neurons to remove the unreasonable neurons and find the neurons at the beginning of the simulation to keep the battery charge between 2% and 5%, where the engine fuel consumption is the lowest as the final optimization result.

3. Establishment of engine optimization model

The model is optimized based on the Matlab/Simulink model[5]. The stability of the engine torque and speed is simulated and analyzed. The comprehensive performance is also analyzed.

4. Simulation analysis

The parameters of the model are optimized using the method previously mentioned. The simulation analysis of the series hybrid car model is carried out by using Matlab. The main parameters are shown in Table 1, in which the road recursion adopts the urban driving condition of the United States, as shown in Figure 1. The parameters of the model were showed in Figure 3, the number of cycle is 1.

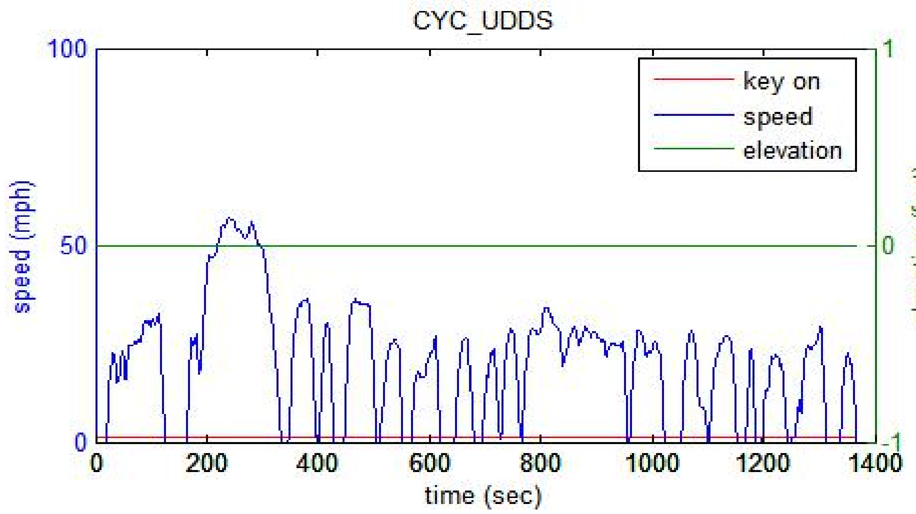
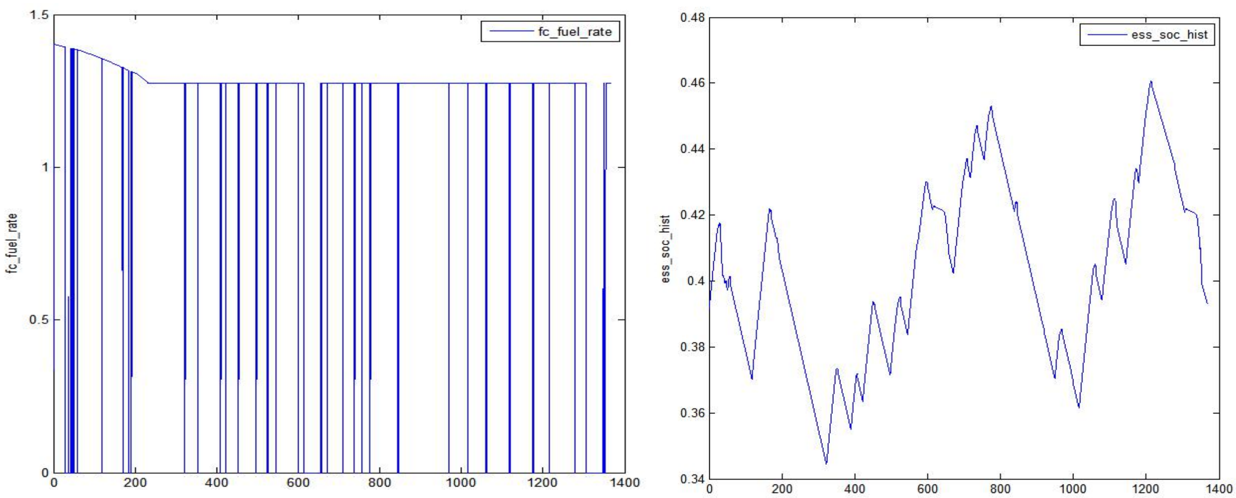


Figure 3 Driving conditions in the United States

a. Speed curve b. Engine output torque curve



c. Fuel consumption rate d. Charge state

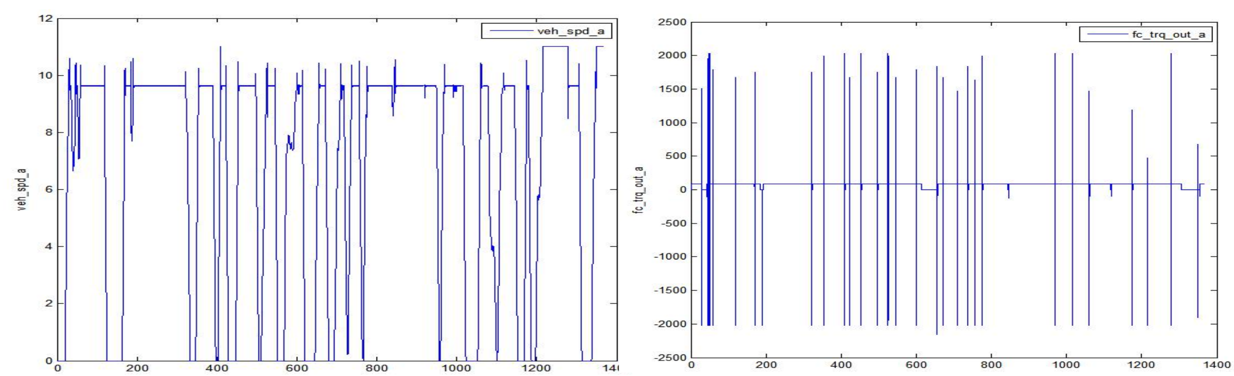


Figure 4 Common energy management strategy performance curve

The simulation results show that the optimized energy management strategy is better than the common strategy. In addition, the energy efficiency of the energy management strategy is better than that of the common energy management strategy. After the energy management strategy is optimized for the engine output torque, the battery charge state improve, the vehicle speed change and the fuel consumption reduced.

Conclusion

The energy management strategy is the key to coordinate the work of the various sub-components of the hybrid car. According to the design of energy management strategy of a series hybrid vehicle, a car model is established based on the powertrain components and vehicle parameters. The dynamic optimization is carried out by using the dynamic programming algorithm and the SQP algorithm is used to solve the problem. Finally, the SOM algorithm is further optimized on the basis of global optimization. In summary, this study provides a global optimization of energy management control strategy based on neural network. This strategy can provide an optimized engine model to provide a database for further optimization of engine performance in the future.

The simulation analysis of the research model, analysis of the optimized energy management strategy and the general global optimization of energy management strategy control by using the Matlab platform results in effectiveness of the control strategy.

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