Research Article

Real-Time Control Strategy of Elman Neural Network for the Parallel Hybrid Electric Vehicle

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Through researching the instantaneous control strategy and Elman neural network, the paper established equivalent fuel consumption functions under the charging and discharging conditions of power batteries, deduced the optimal control objective function of instantaneous equivalent consumption, established the instantaneous optimal control model, and designs the Elman neural network controller. Based on the ADVISOR 2002 platform, the instantaneous optimal control strategy and the Elman neural network control strategy were simulated on a parallel HEV. The simulation results were analyzed in the end. The contribution of the paper is that the trained Elman neural network control strategy can reduce the simulation time by 96% and improve the real-time performance of energy control, which also ensures the good performance of power and fuel economy.

1. Introduction

Under the dual pressure of environmental pollution and energy crisis, hybrid vehicles have advantages of both conventional vehicles and electric vehicles, which have characteristics of energy conservation, environmental protection, diverse shapes, and strong implementation. Hybrid vehicles have become an effective way to solve the problem of energy crisis and environmental protection and also have been one of the most perspective vehicle models.

According to different connective ways of power system, hybrid electric vehicle (HEV) can be mainly divided into four styles: series, parallel, series-parallel, and complex. The dynamic structure diagram is shown in Figure 1.

Engine output energy of series HEV is transformed two times and the efficiency of the motor and generator is relatively low, so series HEV loses more energy and leads to lower efficiency than vehicles of internal combustion engine. Parallel HEV (PHEV) is equipped with series and parallel power systems, and their structures and control systems are more complex and have higher cost. Complex HEV structures and control systems are most complex and have highest cost. However, parallel hybrid power system can adapt to various road conditions and is widely used by enterprises [1, 2].

As the core of multiple energy control system, the energy control strategy determines performances of PHEV. Based on vehicle’s torque, energy control strategies of PHEV are mainly divided into four types [3, 4]: static logic threshold energy control strategy, instantaneous optimal energy control strategy, global optimal energy control strategy, and neural network energy control strategy. The static logic threshold control strategy cannot guarantee the optimal fuel consumption of PHEV, does not adapt to dynamic conditions, and cannot make the whole system to achieve maximum efficiency. Besides, its threshold parameters are set by engineering experience [5, 6]. The global optimal control strategy can achieve global optimal fuel consumption of HEV. Its defects are complex algorithm, large amount of calculation, and knowing the whole condition in advance [7, 8]. Neural network energy control strategy can adapt to diverse conditions with good robustness and obtain global fuel consumption optimum by engineering experience [9, 10]. Instantaneous optimal energy control strategy can realize minimum equivalent fuel consumption of PHEV in each control cycle which is widely used to distribute PHEV energy [11].
The basic principle of instantaneous optimal control strategy is based on the model of the optimal curve of engines; the object function of the whole power system was optimized on the specific operating points of parallel HEV. On the basis of the instantaneous optimal operating points, it makes power of variable states redistributed and make the loss of energy minimized in the energy flow process at any time (see Figure 2). Instantaneous optimal control strategy has good fuel economy at any time and bad real-time performance. Its real-time performance is influenced by these factors which are the accuracy of various components battery ages and engine and motor characteristics [12–14]. So it is difficult to improve the real-time performance of instantaneous optimal control strategy by changing these factors.

The hybrid vehicles possess good power performance and fuel economy and obtain rapid allocation energy by finding a new energy control strategy. Elman neural network is a feedback neural network and has a very strong computing ability and stability [15]. The instantaneous rules of the instantaneous optimal control strategy are used to train Elman neural network, establish Elman neural network controller, and improve the real-time performance of energy control [14–16].

Based on the research of the instantaneous optimal control strategy, the strategy possesses good fuel economy and makes energy distributed reasonably. However, its real-time performance is poor. In order to solve bad real-time defects of instantaneous control strategy, instantaneous optimal control rules are used to train the Elman neural network control strategy and improve the real-time performance of the trained Elman energy control strategy on the premise that it can guarantee advantages of the instantaneous optimal control strategy. The results show that the trained Elman neural network control strategy can replace the instantaneous optimal control strategy, optimize power distribution, and make the simulation time reduced by 60%.

2. Research Energy Control Strategy

2.1. Instantaneous Optimal Control Strategy. Instantaneous optimal control strategy is defined as follows. In order to achieve the minimum fuel consumption of HEV, the optimal output power of the engine and electric motor is calculated in each control cycle of hybrid power system. Working conditions of HEV and calculation expressions of the equivalent fuel consumption are different in every time. So an optimal objective function should be established [17]. Working condition of hybrid system is divided into two cases of power battery charging and discharging. Then, objective functions of the instantaneous equivalent minimum fuel consumption were established on two working conditions.

Here, the full line represents the circulation and transformation of fuel chemical energy in the hybrid power system. The dotted line represents electric current circulation and transformation in the hybrid power system.
2.1.1. Calculate the Equivalent Fuel Consumption of Battery Discharging. When the power battery takes part in driving hybrid cars, its SOC value will reduce and deviate from the target of SOC value. In order to compensate for the used electricity and restore SOC value of power batteries, the engine drives the motor to charge power batteries in the future time [18]. The charging time is divided into \( n \) control cycles, and the motor power of each cycle is \( P_{mc,chg,i} \) (\( i = 1, 2, 3 \ldots, n \)) [5].

The relationship between the motor power \( P_{mc} \) with driving vehicle and the motor power \( P_{mc,chg} \) with power batteries charging is

\[
P_{mc} = \eta_{mc} \eta_{dischg} \eta_{chg} \sum_{i=1}^{n} P_{mc,chg,i},
\]

where \( \eta_{mc} \) is the average efficiency of motor; \( \eta_{chg} \) is the average efficiency of power battery charging; \( \eta_{dischg} \) is the average efficiency of power battery discharging.

When the motor drives the vehicle, the energy consumption of power batteries can be converted into the engine fuel consumption. The equivalent fuel consumption rate of the motor is

\[
b_{mc,eq} = \sum_{i=1}^{n} \left( P_{fc,i} \eta_{chg} - P_{fcN2,i} \eta_{chg} \right),
\]

where \( P_{fcN2,i} \), when the engine does not charge power batteries, is the engine power of the \( i \) control period; \( b_{N2,i} \), when the engine does not charge power batteries, is the fuel consumption rate of the engine; \( P_{fc,i} \), when the engine charges power batteries, is the engine power of the \( i \) control period; \( b_{chg} \), when the engine charges power batteries, is the fuel consumption rate of the engine.

Let \( \bar{b}_{chg} \) be the average fuel consumption rate when the engine charges power batteries:

\[
\bar{b}_{chg} = \sum_{i=1}^{n} \frac{P_{fc,i} \eta_{chg} - P_{fcN2,i} \eta_{chg}}{P_{mc,chg,i}}.
\]

Merge (3) and (2):

\[
b_{mc,eq} = \frac{\bar{b}_{chg}}{\eta_{chg} \eta_{dischg} \eta_{chg}}.
\]

When the motor drives the vehicle after a period of \( \Delta t \), equivalent instantaneous fuel consumption of the motor is

\[
m_{mc,eq} = \frac{\bar{b}_{chg} P_{mc}}{\eta_{chg} \eta_{dischg} \eta_{chg}}.
\]

2.1.2. Calculate the Fuel Consumption of Batteries Charging. When the power battery is charged by the engine, its SOC value will rise and even exceed the target of SOC value. In order to maintain SOC values, power battery energy will be consumed in future [18]. Discharging time is divided into \( n \) control cycles, and the motor power of the each control cycle is \( P_{mc,chg,i} \) (\( i = 1, 2, 3 \ldots, n \)) [17].

In a certain period of discharging time, the relationship between motor power \( P_{mc,chg} \) with driving vehicle and motor power \( P_{mc,chg,i} \) with charging power batteries is

\[
\sum_{i=1}^{n} P_{mc,chg,i} = P_{mc,chg} \eta_{chg} \eta_{dischg} \eta_{chg}.
\]

where \( P_{mc,chg} \) is the motor power when the power battery is charged; \( \eta_{chg} \) is the average efficiency of motor; \( \eta_{dischg} \) is the average efficiency of the power battery charging; \( \eta_{chg} \) is the average efficiency of the power battery discharging.

When the motor drives the vehicle, the relationship between the motor power battery energy consumption and the fuel consumption rate is

\[
b_{mc,eq} = \frac{P_{fc,i} \eta_{chg} - P_{fcN2,i} \eta_{chg}}{P_{mc,chg} \eta_{chg} \eta_{dischg} \eta_{chg}}.
\]

Simplify the (8) formula:

\[
b_{mc,eq} = \frac{b_{chg} b_{mc,i} \eta_{chg}}{\eta_{chg} \eta_{dischg} \eta_{chg}}.
\]

When the motor charges power batteries after a period of \( \Delta t \), the objective function of equivalent instantaneous fuel consumption of the motor is

\[
m_{mc,eq} = \frac{\bar{b}_{chg} P_{mc,chg}}{\eta_{chg} \eta_{dischg} \eta_{chg}}.
\]

2.1.3. Deduce the Objective Function of the Instantaneous Optimal Control Strategy. Set two new variables:

\[
f_{eq,chg} = \frac{\bar{b}_{chg} P_{mc,chg}}{\eta_{chg} \eta_{dischg} \eta_{chg}}, \quad f_{eq,chg} = \frac{b_{chg} P_{mc,chg}}{\eta_{chg} \eta_{dischg} \eta_{chg}},
\]

where \( b_{chg} \) is the fuel consumption rate when the engine charges power batteries at the present moment; \( \bar{b}_{chg} \) is the average fuel consumption rate when the engine charges power batteries in the future time.

The instantaneous control objective function of the lowest fuel consumption is

\[
M = \sum \min \left\{ m_{fc} \left[ T_{fc} (t), \omega (t) \right] \Delta t + m_{mc,eq} \left[ T_{mc} (t), \omega_{mc} (t) \right] \Delta t \right\},
\]
where $\omega_c(t)$ is engine speed; $\omega_m(t)$ is motor speed; $T_{fc}$ is output torque of the engine; $T_{mc}$ is output torque of the motor. Consider

$$m_{mc,eq} [P_{mc}(t)] = \begin{cases} f_{eq,dischg} P_{mc} & T_{mc} > 0 \text{ (power batteries discharge)} \\ f_{eq,chg} P_{mc,chg2} & T_{mc} < 0 \text{ (power batteries charge)} \end{cases}.$$  

(13)

$P_{mc}$ and $P_{mc,chg2}$ are both motor power, so they can be unified as $P_{mc}$. By calculating, the improved instantaneous control objective function of the minimum fuel consumption is

$$M = \sum \min \{ m_{fc} [P_{fc}(t)] \Delta t + [M_{eq,dischg} + (1 - \lambda) f_{eq,chg}] P_{mc} \Delta t \},$$

where $\lambda = (1 + \text{sign}(T_{mc}))/2$.  

2.1.4. Improve the Objective Function of the Instantaneous Optimal Control Strategy. SOC value change of batteries and braking energy recovery both have a certain effect on energy control. The optimal function of the working point needs to be improved.

(1) Revise the SOC Value Function of Power Batteries. When power batteries work, their SOC value is maintained at the high efficient range by the reset function, in order to reduce the loss energy in the process of charging and discharging power batteries and make hybrid system keep better performances. The working principle of SOC reset function is as follows. When the SOC value is more than the target region, the hybrid power system will give priority to consuming power battery energy. It does not stop until SOC value decreases to the target region under the effect of the reset function. When the battery SOC value is lower than the target region, the hybrid system will give priority to consuming fuel energy to drive the vehicle and recover the value of SOC. It does not stop until SOC value returns to the target region under the effect of the reset function.

Set $K_{SOC}$ be the variable in the reset function, and the value table between $K_{SOC}$ and SOC value is shown in Table 1.

Based on the Matlab platform and Table 1 data, the fitting curve between $K_{SOC}$ and SOC value is constructed by using fitting curve toolbox, as shown in Figure 3.

Polynomial function of the fitting curve is

$$K_{SOC} = -8866x^7 + 33460x^6 - 52310x^5 + 43730x^4$$
$$- 21010x^3 + 5766x^2 - 833.5x + 49.77,$$

(15)

where $x$: is SOC value.

Considering the influence of power battery SOC, the formula of instantaneous equivalent fuel consumption of HEV can be expressed as $K_{soc}m_{mc,eq}$.

(2) Revise the Objective Function of Braking Recovery Energy. The adopted method which revises the equivalent fuel consumption function of power battery energy is as follows: the average braking power is calculated at a period of time before the current moment. The power is used as the standard of fuel consumption correction of the braking recovery power in the next moment [19–22].

The statistical time range is divided into $n$ ($n > 0$) cycles. In each cycle, let braking power be a fixed value. Therefore, the average braking power of the whole time can be expressed as

$$\overline{P}_{\text{braking}} = \frac{\sum_{i=1}^{n} P_{\text{braking}_i}}{n}.$$  

(16)

When power batteries discharge, the objective function of instantaneous equivalent fuel consumption is

$$m_{mc,eq} = \frac{\overline{P}_{\text{chg}} (P_{mc} + \overline{P}_{\text{braking}})}{\eta_{mc}^2 \eta_{\text{dischg}} \eta_{\text{chg}}}.$$  

(17)

In summary, taking the influence of power battery SOC and brake energy recovery into consideration, the final
Objective function of instantaneous optimal control strategy is

\[ M = \sum \min \left\{ m_{ic} \left[ P_{fc} (t) \right] \Delta t + K_{soc} n_{eq} \left[ P_{mc} (t) + P_{braking} (t) \right] \Delta t \} \quad (18) \]

### 2.2. Elman Neural Network Control Strategy

2.2.1. The Structure of Elman Neural Network. Elman neural network is put forward by Jeffrey L. Elman in 1990 and is a typical local recessionary grid, as shown in Figure 4 [23].

\( P \) is the input of the neural network and its size is \( R \times 1 \); \( b^1 \) is the neuronal threshold vector of the feedback layer and its size is \( S^1 \times 1 \); \( I W^1 \) is the connective weight vector of the neurons and the input vector in the input layer and its size is \( S^1 \times R \); \( n^1 \) is the middle operational result of the neurons in the feedback layer, namely, weighted sum of the connective weight vector and the threshold vector, and its size is \( S^1 \times 1 \); \( a^1 \) is the output vector of the feedback layer's neuron in the \( K \) iteration and its size is \( S^1 \times 1 \); \( D \) is feedback node. It is the same way that \( b^2, LW^2, n^2, \) and \( a^2 \) are related to parameters of the output layer.

The inputs of structure diagram of Elman neural network is the required torque, speed, and SOC value of power battery and its output is motor torque. The structure diagram of Elman neural network is shown in Figure 5 [24].

The structure diagram of Elman neural network contains input layer, hidden layer, undertaken layer, and output layer. Let the input vector of the input layer be three-dimensional vector \( u \); the output vector of the output layer is one-dimensional vector \( y \); the output vector of the hidden layer is \( n \)-dimensional vector \( x \); the output vector of the undertaken layer is \( n \)-dimensional vector \( r \); \( w^1, w^2, \) and \( w^3 \) are respective connective weights of the hidden layer to the output layer, the input layer to the hidden layer, and the undertaken layer to the hidden layer; \( g(\cdot) \) is the driving function of the output neurons; \( f (\cdot) \) is the driving function of hidden layer; \( h (\cdot) \) is the driving function of undertaken layer; \( \text{net}(\cdot) \) is the net input driving function of a certain layer; \( A \) shows the input layer; \( B \) shows the undertaken layer; \( K \) shows the iterative sequence.

Define two functions:

\[
v_i (k) = \begin{cases} 
    u_n (k), & \text{if } i \in A, \\
    r_n (k), & \text{if } i \in B, 
\end{cases} 
\]

\[
w^j (k) = \begin{cases} 
    w^2, & \text{if } i \in A, \\
    w^3, & \text{if } i \in B. 
\end{cases} 
\]
The input and output functions of the $N$ neuron of the hidden layer are

$$\text{net}_n (k + 1) = \sum_{i \in A \cup B} w^i (k) v_i (k),$$

$$x_n (n + 1) = f (\text{net}_n (k + 1)).$$

The input and output functions of the $N$ neuron of the hidden layer are

$$\text{net}_n (k) = \sum_{i \in A \cup B} w^i (k - 1) v_i (k - 1),$$

$$r (k) = h (\text{net}_n (k)).$$

The input and output functions of the output layer’s neuron are

$$\text{net}_n (k + 1) = \sum_{i \in A \cup B} w^i (k + 1) x_n (k + 1),$$

$$y (k + 1) = g (\text{net}(k + 1)).$$

2.2.2. Select the Parameters of Elman Neural Network. The neuron number is determined by following formula [25]:

$$k = \sqrt{m + n + \beta},$$

where $m$ is the number of the input vector; $n$ is the neuron number of the output vector; $\beta$ is a constant, (1–10).

The excitation function of Elman neural network of the feedback layer selects the Tansig function [26]:

$$\text{tansig} (x) = \frac{2}{1 + e^{-2x}} - 1. (24)$$

2.2.3. Learning and Training Mechanism of Elman Neural Network. Elman neural network is trained by Levenberg-Marquardt algorithm. The error index function of Levenberg-Marquardt arithmetic is

$$E (w) = \frac{1}{2} \sum_{i=1}^{p} \| y_i - y'_i \|^2 = \frac{1}{2} \sum_{i=1}^{p} e_i^2 (w), (25)$$

where $p$ is the sample number; $e_i$ is the systemic error; $y'_i$ is the actual output of the network.

The formula of the adjusting weight is

$$u^{k+1} = u^k + \Delta w.$$ (26)

The computing formula of the increment weight is

$$\Delta w = [J^T (w) J (w) + ul]^{-1} J^T (w) e (w), (27)$$

where $u$ is learning rate; $I$ is the unit matrix; $J (w)$ is the Jacobian matrix. Consider

$$J (w) = \begin{bmatrix}
\frac{\partial e_1 (w)}{\partial w_1} & \frac{\partial e_1 (w)}{\partial w_2} & \cdots & \frac{\partial e_1 (w)}{\partial w_n} \\
\frac{\partial e_2 (w)}{\partial w_1} & \frac{\partial e_2 (w)}{\partial w_2} & \cdots & \frac{\partial e_2 (w)}{\partial w_n} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial e_n (w)}{\partial w_1} & \frac{\partial e_n (w)}{\partial w_2} & \cdots & \frac{\partial e_n (w)}{\partial w_n}
\end{bmatrix}.$$ (28)
Error value $\varepsilon$, constant $\beta$, and $\mu_0$
initialization: $K = 0$, $\mu = \mu_0$

Calculate network outputs and error
index function $E(w^k)$

Order $k = k + 1$
$\mu = \mu \beta$

Calculate Jacobian matrix $J(w^k)$

Calculate the weight increment $\Delta w$

Calculate the $k + 1$ iteration weights $w^{k+1}$

Calculate $E(w^{k+1})$

Order $\mu = \mu / \beta$

$E(w^{k+1}) < E(w^k)$

Yes

$E(w^k) < \varepsilon$

Yes

Terminate

No

No

Figure 6: Process map of the adjusting network weight.

Table 2: Parallel hybrid electric vehicle parameters.

| Parameter                  | Value          |
|----------------------------|----------------|
| Curb weight                | 1605 kg        |
| Face area                  | 2.65 m$^2$     |
| Wheel base                 | 2.775 m        |
| Height of the center of mass| 0.5 m         |
| Front axle load distribution ratio | 0.51 |
| Coefficient drag           | 0.32           |
| Engine                     |                |
| Peak power                 | 118 kW         |
| Displacement               | 2.5 L          |
| Power battery pack         |                |
| Voltage                    | 244.8/650 V    |
| Style                      | NI-MH          |
| Volume                     | 6.5 Ah         |
| Mold number                | 34             |
| Motor                      |                |
| Peak power                 | 105 kW         |
| Style                      | PMSM           |

Table 3: Traffic parameters of simulation experiments.

| Parameter                  | NEDC   | HWFET   |
|----------------------------|--------|---------|
| Idle time (s)              | 298    | 6       |
| Top speed (km/h)           | 10.93  | 16.51   |
| Cycle time (s)             | 1184   | 765     |
| Average speed (km/h)       | 33.21  | 77.58   |
| Maximum acceleration (m/s$^2$) | 1.06 | 1.43 |
| Maximum deceleration (m/s$^2$) | $-1.39$ | $-1.48$ |
| Park time (time)           | 13     | 1       |
| Traveling distance (km)    | 120    | 96.4    |

As shown in Figure 13(a), Elman neural network strategy can make the engine produce more torque than the instantaneous optimal control strategy at the beginning of 600 s on the NEDC working condition. It can make the vehicle start, accelerate, and climb better. After the vehicle starts, the two control strategies play the same role on the vehicle energy control. As seen in Figure 13(b), Elman neural network strategy can make the engine produce slightly more torque than instantaneous optimal control strategy on the HWFET working condition, while these two strategies have similar effect on the engine torque control.

As seen in Figure 15, Elman neural network strategy can make motor produce slightly more torque than the instantaneous optimal control strategy at some moments on the NEDC and HWFET working condition, while the two strategies have the similar effect on the motor torque control.

As shown in Table 4, compared with the instantaneous optimal neural strategy, fuel consumption of Elman neural network strategy only increases about 0.5 (L/100 km) on the NEDC and HWFET working condition, which implies that Elman neural network controller can also have the
advantage of low fuel consumption. The slight increase in fuel consumption can be accepted since it has a little effect on the fuel economy of the whole vehicle. As seen in Table 5, Elman neural network strategy makes the simulation time decreased greatly compared with the instantaneous optimal neural strategy and improves the response time of the vehicle greatly.

Table 4: Fuel consumption of 100 km (L/100 km).

| Strategy               | Road  | NEDC | HWFEF |
|------------------------|-------|------|-------|
| Instantaneous optimal control | 9.4   | 6.5  |
| Elman neural network    | 9.8   | 7    |

Table 5: Simulation time (s).

| Strategy               | Road  | NEDC | HWFEF |
|------------------------|-------|------|-------|
| Instantaneous optimal control | 471.3 | 315.8|
| Elman neural network    | 15.6  | 10.2 |

In conclusion, as seen in Figures 13, 14, and 15, Elman neural network strategy can replace the instantaneous optimal control strategy to maintain SOC value at the high efficient range and achieve a reasonable distribution of the torque between the engine and the motor. The significance of the
Initialize weights  
Input sample values  
Calculate output values of the input layer  
Calculate output values of the hidden layer  
Calculate output values of the undertaken layer  
Calculate output values of the output layer  
Calculate error functions  
Update weights  

Figure 11: The training flow diagram of the trained Elman neural network.

Figure 12: Simulation model of the parallel hybrid electric vehicle.

(a) NEDC working condition  
(b) HWFET working condition  

Figure 13: Contrast power battery SOC.
paper is that the simulation time of energy control is reduced by 96%.

5. Conclusion

Through the research on the instantaneous optimal strategy and Elman neural network control strategy, we deduce the objective functions of instantaneous optimal control and establish the instantaneous control model and design the Elman controller. Based on the ADVISOR 2002 platform, two control strategies were simulated on a hybrid electric vehicle.

It is seen from the simulation results that the trained Elman neural network strategy shows similar control ability on the vehicle energy distribution compared with the instantaneous optimal control strategy, which ensures good performances of power and fuel economy of HEV, reduces the control reaction time greatly, and overcomes the disadvantage of poor real-time performance of the instantaneous optimal control strategy. The research significance of the paper is that the simulation time of energy control is reduced by 96%. Future works are listed as below.

(1) Simulation and experiment should be improved by adding more design parameters, such as vehicle emission.

(2) It is necessary to do lots of experiments to enrich simulation results.

(3) Actual road condition is more complex than the simulation road condition, so control strategies need to be tested in the actual road conditions.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.
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