Predictive Energy Management for Hybrid Electric Vehicle Considering Driver’s Intention

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Abstract

The driver’s intention determines the vehicle’s Macro-driving state. On the premise of ensuring that the driving state of the vehicle conforms to the driver’s intention, it is of practical significance to study the energy-saving of the vehicle. Through the correlation analysis of acceleration / brake pedal signal with vehicle speed and acceleration under real working conditions, the strong correlation between driver input and vehicle speed appears in the range of 4-6 seconds. The mapping relationship between driver’s intention and driver’s expected speed is constructed by extreme learning machine. Based on this, the model predictive control for hybrid electric vehicle is carried out. It is compared with the global optimal control strategy solved by dynamic programming and the instantaneous optimal control strategy under the same discrete precision. The results show that compared with the instantaneous optimal control strategy, model predictive control based on driver’s intention can save 9.92% of the energy consumption while meeting the driver’s intention (RMSE 0.9995m/s).

Keywords: model predictive control, driver’s intention, extreme learning machine network, energy management

Nomenclature

Abbreviation
MPC Model Predictive Control
ELMN Extreme Learning Machine Network
IOC Instantaneous Optimal Control
DP Dynamic Programming
RMSE Root Mean Squared Error
MSE Mean squared error
MRE Mean Relative Error
R2 Coefficient of Determination
r Correlation coefficient

Introduction

The rising concern about global energy crisis and its impact on the environment implies a transition from the current development paradigm to a sustainable one, which remains a significant challenge for scientists, industries and government to make reasonable energy and environmental policies to save energy and reduce environmental impact as well as carbon emission during the managing and controlling process at each level of the concerned ecosystems. There is already plenty of discussion about these problems, along with an abundance of journals with disciplinary territories and sharp boundaries on the intellectual landscape, some of which may prove to be valuable. However, we need a problem-oriented forum, not a discipline-based one, for putting the pieces together, promoting intelligent discussion of an integrated vision of human and natural world.

In the process of vehicle driving. The inputs, which include Acceleration, braking and steering, of the system are mainly generated by the driver, when Vehicle Speed is taken a State Quantity of the system. Due to the small proportion of the energy consumed in the steering process in the driving process, only the situation of driver’s acceleration and braking are considered.

Vehicle driving process is a link of person-vehicle-road interaction. Generally, we focus on driver modeling to achieve the judgment of driver’s intention, and then carry out the energy management of driving process [1, 2]. Alternatively, global optimal energy management can be achieved through condition identification [3, 4]. However, when the driving behavior is complex or the parameters of the identification process are not properly selected, the modeling often fails to achieve good prediction results [5, 6].

In this paper, in order to build the driver’s intention mapping network, the black box model is established,
which simplifying the analysis of driver's behavior. On this mapping network, the energy strategy based on driver's intention is studied. And the process is as follows:

1) Installing the Data Collection System for Vehicle System. Collecting the data of vehicle driving (vehicle speed, GPS coordinates, etc.), bus data (acceleration pedal signal, brake pedal signal, battery SOC, etc.);

2) Analyzing the data of the acceleration pedal signal, brake pedal signal and vehicle speed signal, and filtering anomalies and noise of signal;

3) Through correlation calculation, analyzing the offset of vehicle system to accelerating pedal signal and braking pedal signal, and determining the appropriate time of historical signal data and predictive horizon.

4) Taking the acceleration signal, brake pedal signal and vehicle speed signal as input of ELMN (extreme learning machine network), obtaining the driver's intention;

5) Comparing the results of MPC energy management strategy based on driver's intention, DP (dynamic programming) strategy and IOC (instantaneous optimal control) strategy.

2 Correlation Analysis

The configuration of the hybrid electric vehicle studied is shown in Fig. 1. Fig. 2 shows one of the historic trajectories of the vehicle in Beijing. Fig. 3 shows a three-dimensional figure of the speed and position corresponding to the driving route. And the Data sampling frequency is 10Hz.

![Fig. 1 The configuration of the hybrid electric vehicle](image1)

![Fig. 2 Historic trajectories in Beijing](image2)

The driver's intention is expressed by accelerator pedal signal and brake pedal signal. Fig. 4 shows the acceleration pedal signal, brake pedal signal and vehicle speed. Acceleration pedal signal and brake pedal signal data are acquired by CAN bus. Vehicle speed signals are acquired by on-board GPS devices. The accuracy of the differential GPS signal is ±5 cm.

![Fig. 4 Acceleration pedal signal, braking pedal signal and vehicle speed](image3)

In order to obtain acceleration pedal signal and speed, brake pedal signal and speed response relationship, the data of acceleration pedal signal and brake pedal signal are offset. The correlation between acceleration pedal signal and speed, and the correlation between brake pedal signal and vehicle speed are analyzed under different offset conditions. Thus, the prediction horizon of speed prediction based on driver's intention can be determined.

![Fig. 5 Correlation of acceleration/brake signal & speed](image4)
Fig. 6 Correlation of acceleration/brake signal & acceleration

Fig. 5 shows the relationship between the correlation coefficients of acceleration /brake pedal signal and vehicle speed with time offset under different offset. Fig. 6 shows the relationship between acceleration / brake pedal signal and acceleration with time offset. As can be seen from Fig. 5, the highest correlation between speed and acceleration / brake pedal signals is about 3-5 s. From Fig. 6, it can be seen that the correlation between acceleration and brake pedal signal decreases gradually with time.

On the premise that the driver is familiar with the driving characteristics of the vehicle, the correlation analysis of acceleration pedal signal, brake pedal signal and speed shows that the driver's intention to accelerate or brake is about 0~5s. Therefore, the mapping relationship between acceleration or brake pedal signal and future speed can be realized by mapping. The historical data needed for prediction should not less than 5s.

3: Speed Prediction

ELMN, as a kind of feedforward neural network with single hidden layer, has strong ability of non-linear mapping and can converge quickly. In ELM algorithm, once the input weight and the bias of hidden layer are randomly determined, the output matrix of hidden layer is uniquely determined, while the basic gradient-based learning algorithm needs to adjust all parameters in the iteration process. The training of single hidden layer neural network can be transformed into solving a linear system. And the output weight can be determined. So a speed prediction network based on driving intent is established through the structure of ELMN.

According to the vehicle dynamics formula, the current speed is mainly determined by the historical speed and driver input. Therefore, the input of extreme learning machine is composed of historical speed, acceleration pedal signal and brake pedal signal. The data of vehicle speed, acceleration pedal signal and brake pedal signal are collected through real driving conditions. There are 50,000 sets of training data and 10,000 sets of test data. The length of the input historical data is 5s, and the predicted horizon is 5s (50 control units).

Ten thousand sets of data were used as test samples. The effect of speed prediction is shown in Table 1. The predicted results of some sample data are shown in Fig. 7.

![Fig. 5 Correlation of acceleration/brake signal & acceleration](image)

![Fig. 6 Correlation of acceleration/brake signal & acceleration](image)

![Fig. 7 Prediction results of part of sample data](image)

The mean square error (MSE) of the test set is 12.9459 km²/h², and the root mean square error (RMSE) is 0.9995m/s. The coefficient of determination (R2) is 0.9995. The regression effect of fitting is better.

<table>
<thead>
<tr>
<th>Sample size</th>
<th>R²</th>
<th>MRE</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>10000</td>
<td>0.9995</td>
<td>8.91%</td>
<td>12.9459</td>
</tr>
</tbody>
</table>

4 Predictive Energy Management

On the basis of the above research, the predictive energy management based on driver’s intention is studied in the framework of model predictive control, and compared with the global optimal energy management based on DP and IOC.

The cost function of the optimizer is as follows:

\[
J = \sum_{i=1}^{n} \left( m_{\text{fuel}} + \alpha \cdot P_{\text{battery}} + \beta \cdot I_{\text{battery}}^{2} + \gamma \cdot T_{\text{engine}} \right)
\]

Where, \( m_{\text{fuel}} \) is fuel consumption, g/J. \( P_{\text{battery}} \) is battery discharge power, W. \( I_{\text{battery}}^{2} \) battery discharge current, An. \( T_{\text{engine}} \) is engine start-stop judgment. \( \alpha, \beta, \gamma \) are scale factors.

The sum of the first two terms of the cost function represents the equivalent fuel consumption value. The latter two items are designed to reduce vehicle wear and tear. The third one is for battery charge and discharge protection, and the last one is for reducing the number of engine start-stop switching.

The simulation results are shown in Table 2.

<table>
<thead>
<tr>
<th>Method</th>
<th>Distance</th>
<th>Fuel consumption</th>
<th>Initial SOC</th>
<th>Final SOC</th>
<th>Fuel economy</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP</td>
<td>20.704km</td>
<td>0.8678kg</td>
<td>0.5</td>
<td>0.51</td>
<td>100%</td>
</tr>
<tr>
<td>MPC</td>
<td>20.708km</td>
<td>0.9817kg</td>
<td>0.5</td>
<td>0.5</td>
<td>88.4%</td>
</tr>
<tr>
<td>IOC</td>
<td>20.704km</td>
<td>1.0898kg</td>
<td>0.5</td>
<td>0.56</td>
<td>79.6%</td>
</tr>
</tbody>
</table>

As can be seen from Table 2, the energy economy of MPC is very close to that of benchmark soled by DP, which is 88.4%. And it is obviously superior to IOC, saved by 9.92%.

Fig. 8 shows the comparison of engine efficiency under three strategies. It can be seen that, compared with IOC,
the MPC based on driving intent can make the engine work as efficiently as possible, thus realizing the energy saving of vehicle driving process. Compared with DP, although the engine operating points under MPC are mostly in the high efficiency range, the engine is more in working state (maybe the engine start-stop constraints in the cost function make the engine as working as possible), which may be the reason why the fuel consumption of MPC is higher than that of DP. Therefore, the next step should be to increase more effective constraints to achieve further reduction of engine working time.

**Figure 8** Efficiency Distribution of Engine

![Efficiency Distribution of Engine](image1)

**Figure 9** Efficiency Distribution of Motor

![Efficiency Distribution of Motor](image2)

Figure 9 shows the distribution of motor efficiency under three strategies. In the range of motor efficiency above 90%, obviously, only MPC strategy based on driver’s intention has working point. In the efficiency range of 80%~90%, the number of working points of DP and IOC is more than twice that of MPC. Meanwhile, the motor is more in non-working state solved by DP and IOC. Overall, MPC strategy has higher motor efficiency. However, the fuel-saving gain by motor efficiency improvement is weaker than that by engine efficiency improvement, which is the reason why the energy economy of MPC is not as good as DP.

**5 conclusion**

(1) The potential mapping relationship between driving signal and speed could be obtained by the analysis of correlation offset. Through the offset analysis results, the time offset between the driver input and the driver’s expected speed can be obtained without building a specific driver model.

(2) The MPC algorithm based on driver’s intention can provide better fuel effect than IOC strategy on the premise of ensuring that the vehicle driving according to the driver’s intention, and can be used in real driving conditions.

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**Reference**


