An Improved Energy Management Strategy for HEV Based on Driving Condition Prediction Within a Finite Time Horizon

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Abstract

Energy management based on driving condition information or driving condition prediction within a finite time horizon is a way of further improving the fuel economy of hybrid electric vehicles (HEVs). The future power demand of vehicles is predicted by using support vector regression (SVR) and fuel economy is further optimised on-line to acquire the optimal operating points of both engine and motor. According to the speed characteristics, the driving cycle is classified as a certain speed mode by using the K nearest neighbour (KNN) algorithm. By taking the speed characteristics as training data, the prediction model for vehicle speed based on SVR under a certain speed mode is obtained through training by applying partial swarm optimisation (PSO). The PSO-SVR method can greatly improve speed prediction accuracy within a finite time horizon both accurately and efficiently. The power demand within the finite time horizon is calculated and the assigned values of various control variables at every sample time are acquired by using dynamic programming (DP) within a finite time horizon. The research results indicated that the control strategy based on predicted information shows a significantly positive effect in optimising fuel consumption and battery utilisation.

Keywords: hybrid electric vehicles; support vector regression; energy management strategy; partial swarm optimisation; K nearest neighbour algorithm

1. Introduction

The energy management strategy (EMS) of a hybrid electric vehicle (HEV) is important for distributing the power from each component. It can be used to optimise the fuel economy of hybrid vehicles.

Prediction based on previous observation is classified as on-line prediction and off-line prediction. On-line prediction is rolling over time to update prediction. Off-line prediction updates the speed information over a period of time.

The earlier methods of future driving condition forecasting include exponentially varying methods: Borhan et al. [1] assumed that the unknown future driver torque is in exponentially decreasing trend. Prediction using artificial intelligence (AI) methods to acknowledge the vehicle future velocities is effective in on-line prediction. [2]

Li et al. [3] applied K-means clustering to recognise vehicle velocity ranges and select the corresponding stochastic driver model for prediction. Support vector machines (SVMs) also improve the recognition of cycle types and they work well in binary and multiple classifications.

After recognising the specific cycle pattern, the corresponding energy control strategy is selected to save the fuel economy [6]. The use of a Markov chain in predicting driver behaviour is effective [3-7]. Li et al. [4] used an equivalent consumption minimisation strategy (ECMS) based on a stochastic approach for energy management on HEVs. Zou et al. [5] applied reinforcement learning with Markov chain to minimise fuel equivalent consumption with the prediction pattern, the dynamic programming (DP) can be used to optimise fuel economy [10, 11].

For forecasting the velocity directly depending on the input of vehicle velocities, a neural network (NN) working as a black box can meet engineering needs here. The NN is usually applied to predict the speed of the vehicles [8], and is usually applied with a fuzzy model to recover training errors and accelerate the training performance. Sun et al. [9] proposed a novel velocity forecasting method based on artificial neural networks (ANNs). Fotouhi et al. [29] trained a historical velocity–time series with a multi-layer perceptron neural network (MLPNN) to 10 s ahead.

Model predictive control (MPC) can predict the future condition with the first time-step prediction result, the MPC can calculate future states by use of a state space function and optimise the result by using control theories such as Pontryagin’s minimum principle (PMP) [15-17] [10], sequential quadratic programming (SQP) [11], and dynamic programming (DP) [18-21]. MPC [12, 13] is often used in conjunction with fuzzy logic or pattern recognition [14-16] to select appropriate operating modes for the current state of the vehicle.

The EMS of the vehicle is mainly based on two directions, the rule-based energy management control strategy and the fuel optimisation-based energy management control strategy [17-19].

2. EMS based on parallel-series HEVs

The result of the cycle prediction-based model is applied to EMS for HEVs. In this paper, we applied the parallel-series hybrid electric vehicle.

By predicting the future speed according to the historical speed, the vehicle torque is distributed in the optimal fuel consumption area in advance.

2.1 Architecture of a hybrid power system

A parallel-series HEV is composed of the following components including an engine, two driving motors, a power battery pack, a power coupling mechanism, and
a transmission. Some part of the total power is used to drive the electric generator through the power coupling mechanism and the generated electric power drive the motor rotate. The remaining power is directly transmitted through the mechanical device.

Finally, the mechanical power is coupled with the motor power through the power coupling mechanism and is then transmitted to the wheels through the transmission (Fig. 1).

The HEV works in 4 main modes, namely charge mode, hybrid mode, engine driving mode and electric mode. The hybrid mode includes two operation mode, the low-speed mode and the high-speed mode.

The two modes are judged by the switching speed. When the vehicle actual velocity is greater than \(v_{iH}\), the low-speed mode is shifted to the high-speed mode as shown in Eq.(1)

\[
v_{iH} = f(\sigma) = (27 + 5\alpha); \quad v \geq v_{iH}; \quad \text{Low} \rightarrow \text{High}
\]

\[
v_{iH} = f(\sigma) = (41 + 5\alpha); \quad v \leq v_{iH}; \quad \text{High} \rightarrow \text{Low}
\]

(1)

The power transmission paths under the two modes are separately displayed in Figs 2 and 3.

In the low-speed mode, the motor rotational speed \(w_a\) and \(w_b\) are calculated by planetary input engine speed \(w_e\) and output speed \(w_o\). The motor A torque \(T_a\) and motor B torque \(T_b\) are calculated by engine output torque \(T_o\) and output axle torque \(T_r\) by Eqns.(2) (3).

\[
\begin{align*}
w_a &= \frac{(1+k_1)(1+k_2)}{k_1 k_i} - k_1 \frac{(1+k_1+k_2)(1+k_3)}{k_2 k_i} \quad w_o \\
w_b &= 0 \quad 1+k_3
\end{align*}
\]

(2)

\[
\begin{align*}
T_a &= -\frac{k_1 k_2 i_f}{(1+k_1)(1+k_2)} \quad 0 \\
T_b &= \frac{i_f + k_1 i_f + k_3 i_f}{(1+k_1)(1+k_2)} \quad \frac{1}{(1+k_1)}
\end{align*}
\]

(3)

Similarly, in the high-speed mode, the motor rotational speed \(w_a\), \(w_b\) and the motor torque \(T_a\), \(T_b\) are calculated by Eqns.(4)(5).

Where, \(k_1, k_2, k_3\) correspond to the planetary gear ratio in Figs 2 and 3. \(i_f\) is the gear ratio of front gear. Different mode corresponds to different torques and speeds. Therefore, it is effective to determine the control strategy of torque distribution after the mode is determined.

\[
\begin{align*}
T_a &= k_1 k_i \frac{(1+k_1)(1+k_2)}{k_1 k_i} - k_1 \frac{(1+k_1+k_2)(1+k_3)}{k_2 k_i} \quad w_o \\
T_b &= 0 \quad 1+k_3
\end{align*}
\]

(4)

\[
\begin{align*}
T_a &= -\frac{k_1 k_2 i_f}{(1+k_1)(1+k_2)} \quad 0 \\
T_b &= \frac{i_f + k_1 i_f + k_3 i_f}{(1+k_1)(1+k_2)} \quad \frac{1}{(1+k_1)}
\end{align*}
\]

(5)

\[
\begin{align*}
\eta_A = \psi_A(T_o, w_A); \quad \eta_B = \psi_B(T_o, w_B) \\
P_e = T_o \psi_e(T_o, w_e); \quad T_o = T_a + T_b
\end{align*}
\]

(6)

\[
P_e = V_{oc}(SOC) I_{ma} - I_{ma}^2 R_{ma}(SOC)
\]

(7)

Therefore, the improved cost function in the first step is given by Eq.(8):
\[ J_\theta(x,u) = \min_{w(t)} \int_{t}^{t+1} \{ m_j(w_j(t),T_j(t)) + P_{\text{bin}}(t) - P_j(t) \} dt \] (8)

Then, optimisation is carried out by using a backward recurrence method. During the recurrence stage of the optimisation process, the control and state variables of each step are restricted by the boundary of control variables and the battery SOC.

At the \( \ell \)-th step, to restrict the fluctuation of SOC of battery and fluctuation of engine torque, the weights are \( \omega_\ell \) to be added to minimise the migration cost \( L_{\ell+1} \), as shown in Eq.(9):

\[ J^*_\ell(x,u) = \min_{\omega_{\ell+1}} \left[ \int_{t}^{t+1} \{ m_j(w_j(t),T_j(t)) + L_{\ell+1}(x(i-1),u(i-1)) \} dt + \omega_\ell \{ SOC(i) - SOC(i-1) \}^2 \right] \]

(9)

At the \( P \)-th step (the last step) within the time horizon, to restrict the fluctuation amplitudes of the final and the original SOCs of the battery, weight \( \omega_P \) is added to restrict the SOC of the battery at the last step, as shown in Eq. (10):

\[ J^*_P(x,u) = \min_{w(t)} \left[ \int_{t}^{t+1} \{ m_j(w_j(t),T_j(t)) + L_{\ell+1}(x(i-1),u(i-1)) \} dt + \omega_\ell \{ SOC(i) - SOC(i-1) \}^2 + \omega_P \{ T_i - T_{i-1} \} \right] \]

(10)

Where, \( J^*_P(x,u) \) refers to the cumulative cost function within the time horizon, which is minimised by optimising the cost function at the \( P \)-th step. And the optimal control variables at each moment within the prediction time horizon are calculated by using the backward recurrence method as shown in Eq.(11):

\[ u^*(t) = \arg \min_{u(t)} J^*_P(x(t),u(t)) \]

(11)

According to DP over \( P \) steps, the control decision-making at \((t+1)\) s from the sampling time at the \( P \)-th step within the time horizon for velocity prediction can be calculated by first using forward recurrence, then backward recurrence.

### 3 Construct driving condition prediction model based on SVR

To solve the velocity prediction problem when using a DP algorithm within a finite time horizon; the assigned values of various control variables at a given sampling time are acquired.

For the SVR model, it is necessary to select a proper kernel function for fitting in a high-dimensional space.

**Step 1:** The radial basis function (RBF) is selected to fit the velocity and also the corresponding key parameters of the SVR model are adjusted.

**Step 2:** PSO and SVR are combined to optimise the parameters of the SVR model.

PSO is applied as the iterative optimisation algorithm of the SVR parameters and it can determine the kernel function

**Step 3:** Secondary optimisation is conducted around the optimal solution obtained by the PSO by applying a grid search method to validate the parameters of the SVR model.

**Step 4:** Establish a validation set and then repeatedly modify the prediction parameters through cross-validation according to the predicted results until the prediction error is controlled to within a certain range.

The process of the EMS based on cycle prediction is displayed in Fig. 7.

### 3.1 Data labelling and pre-processing of the SVR

Two types of driving cycles with significant features are taken as the training set of samples.

The specific implementation steps are as follows:

1. The data pre-processing is conducted on the trained dataset of velocities to extract the major features (including short-term acceleration, maximum deceleration, maximum acceleration, etc.).

2. The extracted velocity features are all relative values rather than absolute values of velocity, which guarantees that the changes in velocity, starting at a random velocity, are all included.

3. Velocity prediction within a finite time horizon.

The method of feature mining within, and rolling prediction of, a short-time horizon is applied to predict the future velocity at the next time step.

### 3.2 Evaluation of prediction accuracy of the SVR model

By comparing the change trend of the predicted velocity curve obtained by using SVR with that of the actual velocity curve, the quality of the fitting effect of the model can be acquired.

The major evaluation indices include:

1. \( R^2 \) squared: the standard primary for evaluating regression quality. The velocity under the original driving cycle is set as \( x \); the \( y \) and \( \text{Var} \) separately refer to the predicted velocity of \( x \) and variance. The \( R^2 \) squared calculation is displayed in Eq.(12):

\[ R(x,y) = \frac{\text{Cov}(x,y)}{\text{Var}(x) \cdot \text{Var}(y)} \]

(12)

2. The mean squared error (MSE) is the major standard for evaluating the regression error. By calculating the error between the predicted velocity and actual velocity, the average variance of the error can be acquired as shown in Eq.(13):

\[ \text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - (w \cdot \phi(x_i) + b))^2 \]

(13)

### 3.3 Parameter matching of SVR based on PSO method

SVR consists of support vectors (SVs). The fitting function can be expressed using RBF kernel function as shown in Eq. (14). The RBF kernel function is shown in Eq.(15). The SVR optimisation problem is shown in Eq.(16). Solving the optimal support vector \([w, b]\) to minimize the cost function is shown in Eq.(16). The key to solving this optimization problem is the determination of the parameters of \( C \) and \( \gamma \).

By using the PSO algorithm, the parameter \( \gamma \) (Eq.(15)) of the kernel function and penalty parameter \( C \)
(Eq. (16)) are optimised to maximise the prediction accuracy of cross-validation.

\[
f(x) = \sum_{i=1}^{N} (a_i - c_i^*) \phi(x) + b
\]

\[
\phi(x) = \exp(-\|x - c_i\|^2 / \gamma^2)
\]

\[
\min_\gamma \frac{1}{l} \| w \|^2 + C \sum_{i=1}^{m} (\xi_i + \xi_i^*)
\]

\[
y - \phi(x) \cdot w - b \leq \epsilon + \xi_i
\]

\[
w \cdot \phi(x) + b - y \leq \epsilon + \xi_i^*
\]

\[
\xi_i, \xi_i^* \geq 0
\]

Therefore, cross-validation and calculation of the SVR are also conducted. The PSO method acquires the globally optimal point by simulating the migration and habitat searching behaviours of birds. The optimal point refers to the point with the highest prediction accuracy of cross-validation.

The process of PSO-SVR is expressed by following steps.

**Step 1:** Initialize the particles. Each particle is composed of \([C_i, \gamma_i]\). The subscript \(k\) of the \(x\) refers to the fact that the fitness of the particle at the \(k\) is \(x^* = f(C_i^k, \gamma_i^k)\) in which superscript \(p\) represents the serial number of individuals in each particle swarm. The boundary of the particles is shown in Eq. (17):

\[
i = 1, \ldots, m, j = 1, \ldots, m,
\]

\[
C_i = U_r (C_{i,\text{in}}, C_{i,\text{out}})
\]

\[
\gamma_i = U_r (\gamma_{i,\text{in}}, \gamma_{i,\text{out}})
\]

The velocity of the initialised first-generation individual particles can be expressed in Eq.(18):

\[
v_{c_i} \in [-C_{i,\text{max}} - C_{i,\text{min}} | C_{i,\text{max}} - C_{i,\text{in}}]
\]

\[
v_{\gamma_i} \in [-\gamma_{i,\text{max}} - \gamma_{i,\text{in}} | \gamma_{i,\text{max}} - \gamma_{i,\text{min}}]
\]

**Step 2:** Initialize the first-generation individual particles searching for the location with their optimal fitness (lowest MSE) at a certain migration velocity within the range of \(U_r, U_r\):

\[
x^c_i = \text{MSE}^c_i = f(C_i, \gamma_i)
\]

\[
x^\gamma_i = \min x^\gamma_i
\]

\[
[C_i, \gamma_i] = \arg \min_{C_i, \gamma_i} \text{MSE}^c_i
\]

Where, \(P^c_i\) refers to the location with the optimal fitness of a single particle at an initialised migration velocity within the search area.

**Step 3:** Compare the locations with the optimal fitness of all individual particles within the population, it can be seen that \(P^c_i = \min(x^\gamma_i)\).

**Step 4:** Update the particle velocity.

The velocity of the first-generation particle is updated. According to the optimal fitness of groups and the location with the optimal fitness of individuals, the optimal fitness is sought within the searching area at the updated velocity.

\[
v_{c_i} = \omega v_{c_i} + \Phi r_1 (x^c_i - x_i) + \Phi r_2 (P^c_i - x_i)
\]

\[
v_{\gamma_i} = \omega v_{\gamma_i} + \Phi r_1 (x^\gamma_i - x_i) + \Phi r_2 (P^\gamma_i - x_i)
\]

\[
r_1, r_2 \in (0, 1)
\]

**Step 5:** Applying iterative optimisation for the particle locations.

If \(x^c_i > x^\gamma_i; x^c_i \rightarrow x^\gamma_i\), the locations with the optimal fitness of each individual particle within each population are updated to enable individuals to approach to the location with the optimal fitness. If \(x^\gamma_i > P^\gamma_i; x^\gamma_i \rightarrow P^\gamma_i\).

**Step 6:** The location with the optimal fitness is updated to the final generation to compare the optimal fitness within all generations and we select the value of \([C_i, \gamma_i]\) with the lowest MSE.

By taking Model1 as an example, the discrete operation is conducted within the ranges of \(2^8 - 2^9\) of \(C\) and \(2^9 - 2^{9.8}\) of \(\gamma\). Therefore, according to the results of a grid search, the optimal MSE obtained through cross-validation is determined (Fig. 5). As shown in the result of a grid search, the optimal MSE is 0.207.

By substituting the optimal results of parameters \(C\) and \(\gamma\) obtained through training into the SVR model, the SVR model (Model1) for predicting the first velocity within the future time horizon can be attained.

![Fig. 4 Parameter selection for an SVR model based on PSO algorithm](image1)

![Fig. 5 Parameter matching of model1 based on a grid search](image2)

4 Simulation of control effect and experimental verification

By taking the urban dynamometer driving schedule (UDDS) cycle as an example, the EMS based on finite time domain driving condition prediction based dynamic programming (FTDP) and the ECMS are compared.

During the UDDS cycle, the speed following cycles of vehicles during practical driving trials is favourable, as shown in Fig. 6.
Sort the size of the SOC fluctuation of the DP based energy management: DP1>DP2>DP3>DP4. The DP4 is helpful to maintain the stability of battery SOC with the longest prediction time domain as shown in Fig. 7 in purple line.

FTDP can predict changes in vehicle velocity. On this basis, the operating points of the engine can be densely distributed around the curve of optimal fuel economy, avoiding excessive response from the EMS to the demands of acceleration and deceleration or large loading of vehicles, which results in a waste of fuel.

**5 The Experiment verification**

In this paper, hardware in loop simulation is used to test the energy management strategy. The vehicle model is downloaded to the real-time vehicle simulator, and the energy management strategy is downloaded to RapidECU. They communicate through the vehicle CAN network. The integrated console is composed of a vehicle controller, PC, monitor, and dynamometer controller box data acquisition system as shown in Fig. 10.

<table>
<thead>
<tr>
<th>Cycle</th>
<th>Final SOC (%)</th>
<th>Fuel consumption (L/100 km)</th>
<th>ECM</th>
<th>FTDP</th>
<th>ECM</th>
<th>FTDP</th>
<th>FIR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UDDS</td>
<td>58</td>
<td>22.7</td>
<td>59.7</td>
<td></td>
<td>21.5</td>
<td></td>
<td>5.28</td>
</tr>
<tr>
<td>TC</td>
<td>59.5</td>
<td>27.7</td>
<td>59.8</td>
<td></td>
<td>25.3</td>
<td></td>
<td>8.66</td>
</tr>
<tr>
<td>Hwefet</td>
<td>58.8</td>
<td>20.2</td>
<td>59.2</td>
<td></td>
<td>19.1</td>
<td></td>
<td>5.49</td>
</tr>
<tr>
<td>LA92</td>
<td>56.1</td>
<td>42.6</td>
<td>57.3</td>
<td></td>
<td>40.5</td>
<td></td>
<td>4.92</td>
</tr>
<tr>
<td>NYCC</td>
<td>59.6</td>
<td>5.68</td>
<td>59.8</td>
<td></td>
<td>5.35</td>
<td></td>
<td>5.80</td>
</tr>
<tr>
<td>UNIF</td>
<td>54.2</td>
<td>26.8</td>
<td>55.6</td>
<td></td>
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<td>58.8</td>
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<td>9.45</td>
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<td>9.13</td>
</tr>
</tbody>
</table>

The FTDP and ECMS are both tested under multiple driving cycles (Table 3). The fuel improved rate (FIR) under different regimes are taken as the basis for measurement and also the values of SOCs are compared when ECMS and FTDP are used under various driving cycles to judge whether, or not, the optimal balance of charge and discharge of battery are reached. Based on practical driving cycles, the driving condition-based prediction method and EMS are simulated, and the test results of various state variables are displayed in Figs 21 to 24.
6 Conclusion

By comparing the results to those obtained using ECMS, that the fuel economy of finished vehicles is effectively improved by using the FTDP algorithm is validated. The results showed that the improved control strategy, within a finite time horizon, can improve the fuel economy of the vehicles. Moreover, the coordinated power distribution of engine and motor can reduce the charging and discharging conditions of batteries to a significant extent, thus effectively prolonging battery life.

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8 References