Model building and evaluation for 4-wheel drive hybrid vehicle based on the random forest

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Abstract. In order to improve the accuracy of 4WD hv-pm (hybrid vehicle powertrain model), a virtual controller (VC) is established based on machine learning methods and benchmark data. Considering that developed VC can reflect the real performance of vehicle, the accuracy of 4WD hv-pm is measured by VC output. The machine learning method adopted by VC is random forest (RF), and the preferred benchmark data for building the training set are speed, acceleration pedal, brake pedal, state of charge (SOC), battery current, battery voltage, and traction demand. Moreover, the workable VC can provide engine torque, engine speed, motor torque and motor speed. Therefore, the VC output has been compared with the simulation results of constructed 4WD hv-pm, and the performance difference was evaluated to estimate the accuracy of constructed 4WD hv-pm, so as to further achieve the improvement of the model. Ultimately, it is proved that proposed VCexerts good effect on the effectiveness in model improvement and vehicle development by the means of comparison.

1. Introduction

The 4WD hybrid vehicles achieve better fuel economy through mode switching and engine operating control [1]. Besides, they achieve dynamic coupling through the ground, which can improve the dynamic performance while ensuring economic efficiency [2-4]. In view of the fact that 4WD hybrid vehicles contain multiple power components, and the transient response characteristics of different power components are greatly different, the change of powertrain working state may cause unstable power output under different working conditions, which will have a greater impact on the vehicles and reduce the driving comfort as well. Therefore, it is extremely important to observe the torque output of powertrain in real time.

The 4WD hybrid powertrain is a comprehensive product which integrates mechanical, thermal, electronic, chemical and other disciplines. Its working process is fairly complex and it is difficult to be represented by an accurate dynamic model. Therefore, it is more difficult to identify its working parameters. At present, many scholars at home and abroad have performed plenty of researches on the torque estimation of powertrain by adopting different methods. In reference [5], an exponential function prediction method is used to prove the effectiveness of torque prediction. In reference [6], BP neural network is used to estimate the engine torque, where as it requires large volumes of test data. In reference [7], standard least squares support vector machine (LSSVM) is used for torque prediction, but parameters fail to be optimized. In reference [8], a method of torque prediction is proposed based on motor principle, which optimizes the motor torque control effect, but the effect is unacceptable when motor runs at high speed. In reference [9], a method of least square support vector machine (LSSVM) is used to observe the output torque of dynamic components.
No matter which method is used to observe torque output of hybrid powertrain, a certain number of training samples will be obtained. In the process of obtaining the training samples, training sample accuracy is supposed to be affected due to various errors, such as equipment accuracy error, operator operation error, etc., finally, resulting in the decline of observation accuracy and the failure in conformity with the optimization. Although the training time of data, through support vector machine for regression operation, will increase exponentially with the increasing of data, the problem can be effectively avoided by random forest. In addition, stochastic forest has better robustness than neural network and support vector machine in regression operation, and thus random forest method is adopted. However, since the traditional random forest algorithm mostly uses engineering practice to determine its characteristic parameters, the paper adopts the optimization algorithm to improve the characteristic parameters, so as to ensure better accuracy. Therefore, a virtual controller based on the RF and PSO joint optimization is proposed in the paper. The main innovation points are as follows:

1. Establish a virtual controller based on RF. Vehicle key signals in multiple test data are acted as input, and the demand torque signal of the important power components is used as the output to identify the vehicle motion state.

2. RF is optimized by Improved Particle Swarm Optimization to improve the accuracy of RF regression.

3. The improved RF method is adopted to verify the model accuracy and to observe the crucial dynamic mode switching conditions of the vehicles, which plays a guiding role in the vehicle modeling.

2. Introduction to vehicle configuration

As shown in Figure 1, the powertrain is a 4WD hybrid vehicle composed of the front engine and three motors. The system can realize the switch of series-parallel mode as the system is connected and disconnected by clutch. At the same time, through the adjustment of the front motor, the rear motor and the generator, the working point of the engine is controlled in the optimal efficient zone, in order to reduce the fuel consumption rate and achieve the optimum system efficiency.

![Figure 1. 4WD hybrid vehicle configuration.](image-url)

The hybrid vehicle is mainly divided into electric mode, series mode and parallel mode. In the full electric mode, the front and rear motors output driving torque, then the clutch is disconnected, so the engine and generator shut down. In the series mode, the front and rear motors output driving torque, then the clutch is disconnected, and thus the engine drives the generator to output power. In parallel mode, the front and rear motors are not in working status, and the clutch is connected, so the engine output driving torque, and the generator adjusts its working point.
2.1. Vehicle model construction
The whole vehicle model is built on the MATLAB/Simulink software platform. The model mainly includes driver module, control strategy, load calculation module and vehicle component module.

As shown in Figure 2, the three are connected through CAN lines to complete signal communication.

Figure 2. Vehicle model architecture.

The plant module contains important dynamic component models, such as the front axle motor module, the rear axle motor module, the generator module and the engine module. The engine module is shown as Figure 3.

Figure 3. Switching module under working mode.
With reference to the table, when there are the current engine speed and engine load, the engine module can obtain the current engine output torque. Moreover, the value of the engine output torque plays an important role in judging the driving mode of the whole vehicle. The standard of zero engine torque indicates whether the vehicle is in the full electric mode, and whether the working point of the engine in series mode is diversified. Also, it points out the control strategy of hybrid electric vehicle engine. Therefore, the torque observation accuracy of important parts will affect the determination of mode switching conditions, and the accuracy of mode switching conditions will directly affect the precision of vehicle modeling as well.

3. Set up with PSO-RF virtual controller

Compared with the traditional machine learning, the random forest (RF) has the characteristics of fast computing speed, less computing resource demand and strong generalization ability. However, both the number of decision trees and the number of features selected by the split node have great influence on the effect of the random forest algorithm, so particle swarm optimization (PSO) is adopted. PSO is featured with fast convergence speed and high convergence accuracy.

3.1. A subsection principle of CART regression tree

Given a training sample \( \{ (x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n) \} \), whereunto \( x_i \) and \( y_i \) are the input sample and output sample of training samples respectively.

In the early generation of CART tree, the root node contains all the training samples. The principle of generating CART decision tree is to adopt binary recursion segmentation technique proposed by Breiman L [10-11] et al, that is, to divide the node of each layer according to dichotomy recursively and continuously. Set the number of child nodes of the result to \( i \), in the \( i \) nodes after segmentation of the training sample subset of \( \{ (x_i, y_i) \} \). If the group training sample can output the node of each training sample prediction, the corresponding predicted value is \( \{ p_1, p_2, \ldots, p_m \} \), and \( m \) said the number of nodes and the predicted value is the number of samples. The predicted value corresponding to each node is the mean value of the predicted value corresponding to this node, which can be expressed as

\[
v_i = \frac{\sum_{m'=1}^{m} p_{m'}}{m}
\]

In the formula:
- \( p_{m'} \) is the predicted value of the \( m' \) input sample corresponding to the \( i \) node.
- \( v_i \) is the average of the predicted value of all samples corresponding to \( i \) nodes.

Then the CART tree model can be expressed as

\[
f(x) = \sum_{i=1}^{n} v_i, i \in [1, n]
\]

The training error of the CART tree can be expressed as

\[
e_{rm} = \sum_{i=1}^{N} \left( y_i - f(x_i) \right)
\]

The classification regression tree is used to select the feature and the segmentation value according to the minimum error principle. Assuming that the node cuts the training sample into the training subset \( D_1 \) and \( D_2 \) according to the characteristic \( j \) and cutting value \( s \), the selected features and cutting values should satisfy the minimum mean variances of \( D_1 \) and \( D_2 \) respectively, and the sum of mean variances of both should be minimum, then the above constraint conditions can be expressed as:

\[
\min_{j,s} \left[ \min_{c_1} \sum_{x_i \in D_1(j,s)} (y_i - c_1)^2 + \min_{c_2} \sum_{x_i \in D_2(j,s)} (y_i - c_2)^2 \right]
\]

In the formula:
$c_1$ is the sample output mean of training subset $D_1$.

$c_2$ is the sample output mean of training subset $D_2$.

After repeated binary recursion through the above steps, a complete CART regression tree is generated, that is, the new connected nodes of recursion repeated split nodes reach the maximum until the tree height or the sample number of each node reaches the lower limit.

3.2. Principle of random forest

A single CART regression tree has poor fitting effect under multiple features. However, the use of random forest can effectively improve the fitting accuracy, and its core idea is to optimize the cart tree.

Random forest is a kind of integrated learning, whose essence is to combine bagging random repeat sampling with random subspace method, so as to perfect the integrated learning algorithm of decision tree to optimize its regression effect.

Random repeated sampling of Bagging ensures the regression and generalization ability of a single decision tree. The random subspace method ensures the correlation between decision trees and affects the parallel ability of the random forest processing training samples. Altogether, the two affect the training speed and generalization error of the random forest regression model.

According to the above text description, the random forest regression model is composed of $N$ CART regression trees. Each of which corresponds to a unique random vector $\theta_k$. Then the random forest is the set of regression tree $\{h(X, \theta_k), k = 1,2,\cdots,N\}$, and $k$ is the sequence number of regression tree. For the input quantity, that is, the input sample $X$ of the training sample, the maximum contains different features in $J$, and $Y$ is the output sample of the training sample, both of which are independent. For the prediction model $h(X)$, its mean square generalization error can be expressed as:

$$E_{X,Y} \left( Y - h(X) \right)^2$$

(5)

The total predicted value of the random forest regression model is obtained by averaging the predicted value of $k$ regression trees.

Therefore, there are the following theorems:

Theorem 1: convergence.

$$E_{X,Y} \left( Y - av_k h(X, \theta_k) \right)^2 \rightarrow E_{X,Y} \left( Y - E_{\theta} h(X, \theta) \right)^2$$

(6)

Theorem 2: generalization error bounds.

$$PE^* (\text{forest}) = E_{X,Y} \left( Y - E_{\theta} h(X, \theta) \right)^2$$

(7)

If for all $\theta$, with $EY=E_{X,h}(X,\theta)$, then

$$PE^* (\text{forest}) \leq \rho PE^* (\text{tree})$$

(8)

According to the above principle, the main factor influencing the random forest regression is the number of CART regression trees $N_{tree}$, and the number of node splitting features $M_{ry}$ selected by each tree.

3.3. Principle introduction of PSO

An improved particle swarm optimization (PSO) algorithm is proposed to optimize RF key parameters. In other words, on the basis of the standard PSO, the medium variance and inertia weighting factors of the genetic algorithm are added.

The idea of the standard particle swarm algorithm is to start a group of random particles, then comprehensively analyze and adjust the speed of the particle swarm according to the experience of
individuals and groups, search in the solution space, and finally find the optimal solution through iteration[12]. In each iteration, the particle updates the two values by tracking the maximum pbest of the individual, the optimal solution for the current population, and the global minimum gbest, the optimal solution for the whole population under the current iteration number.

To fix this problem, what needs to be optimized is the number of regression trees treeN, and the number of node splitting features selected by each tree try, so the optimization problem is transformed to search for the optimal solution in two-dimensional space, and the total number is assumed to be m. Whereunto, \( X_i = (x_{i1}, x_{i2}) \) represents the position of the \( i \) th particle and \( V_i = (v_{i1}, v_{i2}) \) represents the corresponding velocity of the particle. When the \( i \) th example is iterated to the point that it has the best fitness, that is, it has reached the optimum. At this point, calcium ion is called the individual optimal particle, denoted as pbest, and when the global particle is iterated to the current best position, it is called the global optimal particle, denoted as gbest. Each particle can be updated according to the following formula

\[
\begin{align*}
    v_{in}^{k+1} &= \omega(k)v_{in}^k + c_1 \times \text{rand} \times (p_{in} - x_{in}^k) + c_2 \times \text{rand} \times (p_{gn} - x_{in}^k) \\
    x_{in}^{k+1} &= x_{in}^k + v_{in}^{k+1}
\end{align*}
\]  

(9)

Type in, \( k \) is the current number of iterations; the \( x_{in}^k \) is the \( i \) th particle of the \( n \)th need to optimize the location of the variables in the first iteration \( k \), and the \( x_{in}^{k+1} \) is its position in the \( k + 1 \) iteration. Similarly, \( v_{in}^k \) is the \( i \) th particles of the \( n \)th need optimization variable in the \( k \) iteration speed, and \( v_{in}^{k+1} \) is its position in the speed of iteration \( k + 1 \), and \( p_{in} \) is the \( i \) th particles in the \( k \) iteration of the variables of the \( n \)th that need to optimize individual extreme value point. In the same way, the \( p_{gn} \) is global extreme value point. \( c_1 \) and \( c_2 \) are learning factors, non-negative constants, used to prevent particles from escaping from solution space, and \( \omega(k) \) is the weight coefficient of inertia.

The above standard particle swarm algorithm is optimized in two aspects, as shown below.

In order to avoid inaccuracy of particle swarm algorithm search and possible optimization to local optimization, the mutation operator is added into particle swarm algorithm based on the idea of variation in genetic algorithm. The aim is to widen the search space of the optimal solution of particle search in the process of iteration and prevent the iteration to local optimum.

The standard particle swarm algorithm generally sets the inertia weighting factor as 1. Seeing that the inertia weighting factor is an important parameter affecting the current particle velocity, larger speed is favorable for global search and smaller speed is favorable for local search. In order to better balance the search capability of the algorithm with the number of iterations, a non-linear decreasing inertial weighting factor is proposed, as shown below.

\[
\omega(k) = \omega_{\text{min}} + (\omega_{\text{max}} - \omega_{\text{min}}) \times \tan \left( 0.875 \times \left( 1 - \frac{k}{k_{\text{max}}} \right)^{k_2} \right)
\]

(10)

In the formula, \( \omega_{\text{max}} \) is the maximum weight of inertia; \( 0.9, \omega_{\text{min}} \) is the minimum weight of inertia; \( 0.3 \); \( k \) is the current number of iterations, and \( k_{\text{max}} \) is the maximum number of iterations. Its flow chart is shown below as Figure 4.
Figure 4. The flow chart of PSO.

4. Comparative analysis of results
To ensure the fairness of the comparison of different machine learning methods, all the training data of different machine learning methods are chosen 11,000 sets, and the verified data are chosen 5,000 sets. Whereof, the value range of the penalty parameter $C$ of the least squares support vector machine is from 0 to 1000, and the value range of the kernel function $\sigma$ is from 0 to 50. Hereinto, the accuracy of the sampled and verified data is shown in the figure.

Table 1. Data obtained with the Measurement.

| Measurement    | Parameter Optimization Method          | RMSE    | MAE    |
|----------------|----------------------------------------|---------|--------|
| F-motor Torque | PSO-RF($N_{tree}$:100,$M_{tree}$:4)    | 0.7961  | 0.2661 |
|                | RF($N_{tree}$:100,$M_{tree}$:3)       | 0.9037  | 0.2710 |
|                | Cross-validation LSSVM                 | 1.1846  | 0.5674 |
|                | BP neural network                      | 1.5391  | 0.8865 |
|                | PSO-RF($N_{tree}$:62,$M_{tree}$:4)    | 2.7969  | 0.9983 |
|                | RF($N_{tree}$:100,$M_{tree}$:3)       | 3.1285  | 1.1002 |
|                | Cross-validation LSSVM                 | 3.5273  | 1.6006 |
|                | BP neural network                      | 4.2464  | 2.2800 |
| ICE Torque     | PSO-RF($N_{tree}$:61,$M_{tree}$:4)    | 1.9054  | 0.3874 |
|                | RF($N_{tree}$:100,$M_{tree}$:3)       | 1.9748  | 0.4340 |
|                | Cross-validation LSSVM                 | 2.2919  | 0.9110 |
|                | BP neural network                      | 2.3925  | 1.1580 |
| Generator Torque| PSO-RF($N_{tree}$:61,$M_{tree}$:4)    |         |        |
|                | RF($N_{tree}$:100,$M_{tree}$:3)       |         |        |
|                | Cross-validation LSSVM                 |         |        |
|                | BP neural network                      |         |        |
As shown in Table 1 and Figure 5, 6 and 7, combined root mean square error (RMSE) and mean absolute error (MAE), it can be concluded that the number of decision trees and the number of split node features have a certain influence on torque observation. At the same time, the article will refer to PSO - RF torque observation and fundamental RF and the cross validation of LSSVM torque observation, to compare and analyze the results with the BP neural network. In terms of error results and comparison of images, improved method of learning random forest have good fitting ability, as the error is small, and the observation accuracy is higher than that with cross validation LSSVM and neural networks. Nevertheless, after optimizing the random forest observer to a certain extent with PSO, its precision is higher than the traditional random forest algorithm. Therefore, the above comparison results and pictures prove the advantages of forest stochastic torque observation and the effect of observer optimization with PSO.
4.1. SIMULINK model verification

According to the engineering practices, the switching conditions of hybrid power four-drive system from full electric mode to series operation mode are only related to the required power of the whole vehicle and battery SOC. Therefore, relevant data of switching from full electric mode to series mode are screened. Furthermore, the remaining variables in the RF are controlled to remain unchanged, and the SOC and speed are increased linearly. The engine torque is shown as Figure 8.

![Figure 8. Torque diagram of ICE.](image1)

As shown in Figure 9, when the battery SOC is less than 37 and the vehicle's required power is greater than 30kW, the engine starts to output torque, and the 4WD hybrid vehicle enters the series mode. When the battery SOC is greater than 37 and the vehicle's required power is greater than 50kw, the engine starts to output torque, and the 4WD hybrid vehicle enters the series mode. So model modification can be done, when the system is in CS mode, and the vehicle power requirement is greater than 30 kW, the 4WD hybrid vehicle composing full electric mode switch turns to serial mode. When the system is in CD mode, and the vehicle power requirement is greater than 50 kW, the 4WD hybrid vehicle composing full electric mode switch turns to serial mode. It can be preliminarily concluded that when system in CD stage series mode, the engine in a single point of control state.

Similarly, the test data of the vehicle switching from series mode to full electric mode is selected. The remaining variables in the RF are controlled to remain unchanged, and the vehicle speed is increased and reduced linearly by SOC accordingly. The engine torque is shown as Figure 9.

![Figure 9. Torque diagram of ICE.](image2)

As shown in Figure 9, when the battery SOC is less than 37 and the vehicle power requirement is less than 12 kW, engine starts to output torque, and the hybrid all-wheel-drive system goes into full electric mode. When the battery SOC is more than 37 and the vehicle power requirement is less than 40 kW, engine starts to output torque, the hybrid all-wheel-drive system goes into the full electric mode. So model modification can be done, when the system is in CS mode and the vehicle power demand is less than 12 kW, the hybrid all-wheel-drive system composing a series mode switch turns to the full
electric mode. When the system is in CD mode, and the vehicle power demand is less than 40 kW, the hybrid all-wheel-drive system by serial mode switch can turn to the full electric mode.

5. Summary
In this paper, a method of building virtual torque observer based on PSO-RF based on vehicle data is proposed. Compared with the standard BP neural network, traditional RF and LSSVM uses cross-validation for parameter optimization in that it has higher observation accuracy and provides a new solution for vehicle controller modeling. In addition, it can be used to analyze the vehicle strategy and correct the vehicle model. Consequently, the author will conduct further research on the deep application of torque observer and the selection of RF optimization method.

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