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Combined Prediction for Vehicle Speed with Fixed Route

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Abstract

Achieving accurate speed prediction provides the most critical support parameter for high-level energy management of plug-in hybrid electric vehicles. Nowadays, people often drive a vehicle on fixed routes in their daily travels and accurate speed predictions of these routes are possible with random prediction and machine learning, but the prediction accuracy still needs to be improved. The prediction accuracy of traditional prediction algorithms is difficult to further improve after reaching a certain accuracy; problems, such as over fitting, occur in the process of improving prediction accuracy. The combined prediction model proposed in this paper can abandon the transitional dependence on a single prediction. By combining the two prediction algorithms, the fusion of prediction performance is achieved, the limit of the single prediction performance is crossed, and the goal of improving vehicle speed prediction performance is achieved. In this paper, an extraction method suitable for fixed route vehicle speed is designed. The application of Markov and back propagation (BP) neural network in predictions is introduced. Three new combined prediction methods, all named Markov and BP Neural Network (MBNN) combined prediction algorithm, are proposed, which make full use of the advantages of Markov and BP neural network algorithms. Finally, the comparison among the prediction methods has been carried out. The results show that the three MBNN models have improved by about 19%, 28%, and 29% compared with the Markov prediction model, which has better performance in the single prediction models. Overall, the MBNN combined prediction models can improve the prediction accuracy by 25.3% on average, which provides important support for the possible optimization of plug-in hybrid electric vehicle energy consumption.

Keywords: Plug-in hybrid electric vehicles, Energy consumption, Vehicle speed prediction, Markov, BP neural networks, Combined prediction model

1 Introduction

Plug-in hybrid electric vehicles (PHEVs) are gradually becoming the main mode of transportation to replace fuel vehicles. Energy-saving and emission reduction has received increased attention [1, 2]. Energy management is a key technology, necessary to improve PHEVs fuel economy [3, 4]. The rule-based energy management strategy is mature [5, 6]; however, it has a lot of restrictions, such as the changes in vehicle parameters, driving conditions and driver habits [7, 8], and difficulty achieving significant

optimization results. The optimized energy management strategy can achieve better control effects for improving vehicle fuel economy [9], but the real-time performance of the strategy is poor. For example, the global optimization control can optimize the most reasonable energy management strategy under the condition of grasping the overall driving conditions [10]. However, the actual driving conditions cannot be obtained during vehicle travel; therefore, the application of the optimized energy management strategy is limited. The development of intelligent transportation systems has provided opportunities for improving the performance of energy management strategies for PHEV [11]. Considering the characteristics of the abovementioned energy management strategies, a predictive control [12, 13], with both optimization

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and real-time, is presented and widely followed, which is based on the predictive energy management strategy [14, 15]. Furthermore, the vehicle speed prediction model becomes a necessary module.

The vehicle speed prediction model can be divided into real-time learning and offline learning. Each model is most suitable for different types of problems. Real-time learning [16] is a data prediction model for online learning. Offline learning [17] is a data prediction model based on historical data. Real-time learning is more varied and offline learning is simple to use, but the real-time learning build environment is more complex when developing energy management strategies. Nowadays, people's lives are gradually regularized. Vehicles, as a means of transportation for people's daily travel, are on a fixed route. With the passage of time, the vehicle speed data on the fixed route begins to reflect the characteristics of the fixed driving cycle. The offline learning model perfectly reflects these inherent characteristics after incorporating this feature. Therefore, it is not necessary to repeat real-time learning of vehicle speed data on the fixed route. In this case, offline learning is more appropriate than real-time learning.

For the study of offline learning models, two commonly used models are utilized, namely, random prediction represented by Markov [18] and machine learning represented by a neural network [19]. Ref. [20] proposed a vehicle speed prediction method based on driving data, using deep learning of a neural network to predict future short-term vehicle speed. However, deep learning relies heavily on driving data, and the prediction accuracy will drop sharply because of driving data that occurs outside of learning. Ref. [21] proposed three methods for vehicle speed prediction based on neural networks, BP, layer recurrent (LR), and radial basis function (RBF). However, the prediction power of neural networks is limited by fitting, and the prediction error is a little large, such that the RMSE is about 2.28 km/h. Ref. [22] designed a high-order Markov velocity predictor combined with a linear programming algorithm, and the speed prediction accuracy was significantly improved compared with the first-order Markov. Although the predicting vehicle speed within the training speed can ensure high accuracy, the predicted vehicle speed outside the training speed cannot be followed well. In this case, the prediction accuracy is 4.47 km/h, which is relatively large. Ref. [23] designed an algorithm based on the velocity constrained Markov stochastic model to predict vehicle speed. The generated velocity trajectory was used to predict the speed of each cycle on the fixed route ahead, but the predicted velocity error is large, such that the RMSE is about 3.8 km/h. Ultimately, prediction accuracy has become a key issue in predictive models. In a word, achieving accurate vehicle speed prediction is a challenge.

From the above research, it can be found that many vehicle speed prediction models have their advantages, but also reflect their shortcomings. For example, contradiction between the high accuracy and generalization exists in the vehicle speed prediction model of the neural network structure; Markov is good at grasping the global speed change state, but the prediction accuracy is poor. Therefore, the research can proceed toward the direction of exploring the advantages of each prediction model to form a new combined prediction algorithm. However, in recent years of research on vehicle speed prediction, the combined prediction model has been rarely studied. Ref. [24] uses a neural network model based on historical speed to predict the average traffic speed of a road segment. Then, the Hidden Markov models (HMMs) are used to represent the statistical relationship between the average vehicle speed and the vehicle speed. However, the prediction curve derived from the combination is not very good.

This paper intends to make full use of the characteristics of Markov and BP neural network prediction models to form a combined prediction model. The predicted vehicle speed obtained from Markov with the characteristics of the following state of speed change, and then local high-accuracy fitting through the BP neural network, will be utilized to obtain better prediction results of the vehicle speed than the two prediction methods. The arrangement of this article is as follows: The second part introduces the source of road driving cycle data used by the prediction model. The third part describes the vehicle speed combined prediction model and the Markov speed prediction model, as well as the BP neural network model used in the model. The fourth part shows the effect of the vehicle speed prediction model and analyzes the characteristics of the prediction model. Finally, the fifth part draws conclusions.

2 Driving Cycle Data Acquisition

The data acquisition experiment of road driving cycle needs to be carried out in the actual traffic environment. Nowadays, people's lives are relatively regular, and it is more common to travel on a fixed route in daily life. The paper decides to select the driving condition information extracted by a fixed route as the data foundation of the research [25], which can reduce the amount of data used by the model and improve work efficiency. Vehicle speed data with multiple features is not the focus of this paper. According to the research needs, a modified vehicle equipped with a global positioning system (GPS) is used to obtain road driving cycle.

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Figure 1 Experimental section and driving route

The route selected in the paper is the travel route commonly used by the population in the region. In order to facilitate the extraction of experimental data, the one-way travel plan is replaced by a round-trip cycle plan, which can also reflect the vehicle speed characteristics of the route. The characteristics of the route selected by the experiment are that there are many pedestrians and deceleration zones on the road, the traffic volume is small, and the driving speed of the vehicle is not allowed to exceed 60 km/h. Because the modified test car is not allowed to drive on the city road, a section of road in Yanshan University is selected as the test route. Experimental equipment is used to extract vehicle speed and GPS location information on this test route, as shown in Figure 1. The vehicle is traveling from the starting point and drives around until reaching the initial position, while the driving trajectory will be generated and the vehicle speed can be collected. In the experiment, it should be noted that the vehicle speed with a fixed step size is extracted within a fixed time interval, which is beneficial to reduce the complexity of the data. Elimination of duplicate data can improve subsequent prediction efficiency, and it paves the way for the construction of the prediction model.

On the basis of the above experimental methods, it is also necessary to repeat the experiment several times at a fixed time every day to obtain sufficient speed characteristics of the route. Some of the vehicle speed data is plotted as shown in Figure 2. It can be seen from the figure that it takes about 10 minutes to perform a driving cycle on this section, and the maximum speed during the driving cycle does not exceed 45 km/h. The speed-distance relationship curve after integration processing is shown in Figure 3. Different sections will begin to show a fixed speed characteristic, which is the characteristic of the road driving cycle. Finally, the received vehicle speed data is collated, combined,

Figure 2 Driving speeds under the fixed route

Figure 3 Fixed route driving speed-distance curves
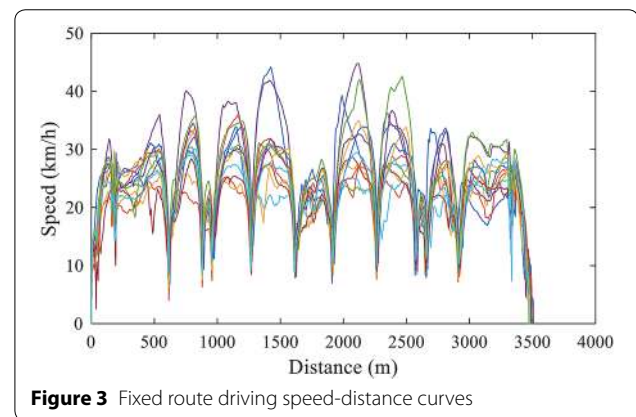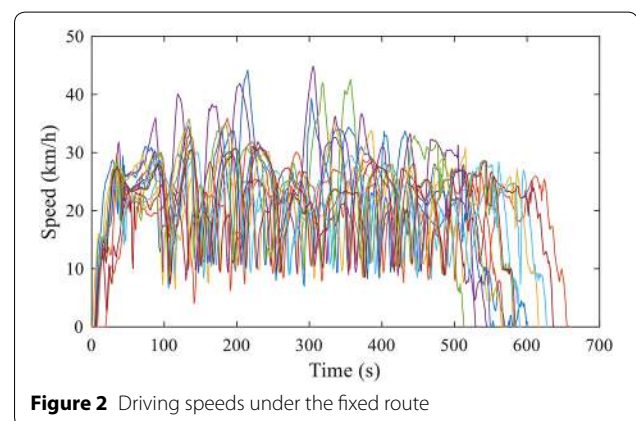
and segmented for use in predictive models. The road condition data obtained will become the basis of the prediction model and support the verification of the accuracy of the prediction model.

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3 Vehicle Speed Prediction Algorithm

For vehicles on a given route, mathematical statistics and machine learning methods, based on historical driving data, can be used to predict future speeds, such as neural networks [26, 27]. It is also possible to predict future speeds by means of random prediction, such as Markov [28]. The following discusses research on the vehicle speed prediction model.

3.1 Markov Prediction Algorithm

Markov is a stochastic process that is widely used as an effective predictor in engineering [29]. The Markov prediction process is as shown in Eq. (1), where $X(t_m) = x_m$ indicates the current state value, $P\{\}$ indicates the state set, $X(t_{m+h}) = x_{m+h}$ indicates the future state value, and $X(t_1) = x_1$, $X(t_2) = x_2, \ldots$, indicates the historical state value. The formula illustrates the non-positive nature of the process, that is, inferring any state in the future based on the current state, and is not directly related to past historical states. The future state of the vehicle has a strong randomness and non-aftereffects. For example, the previous driving state has no direct influence on the current driving state, so the vehicle driving state has Markov characteristics [30].

$$p\{X(t_{m+h}) = j | X(t_1) = x_1, X(t_2) = x_2, \ldots, X(t_m) = x_m\}$$
$$= P\{X(t_{m+h}) = j | X(t_m) = x_m\}, j \in I, \forall h > 0. \quad (1)$$

The steps of Markov prediction can be divided into state division, calculation of transition probability, decision transfer, and prediction [31]. First, according to the multiple sets of vehicle speeds of the fixed route, the speed and acceleration state distribution of the vehicle per second are shown in Figure 4. The vehicle state under this route is basically distributed between 0–45 km/h and the acceleration is distributed at $-3 \sim 3$ m/s^2.

According to the distribution characteristics of vehicle speed and acceleration, the vehicle state in this

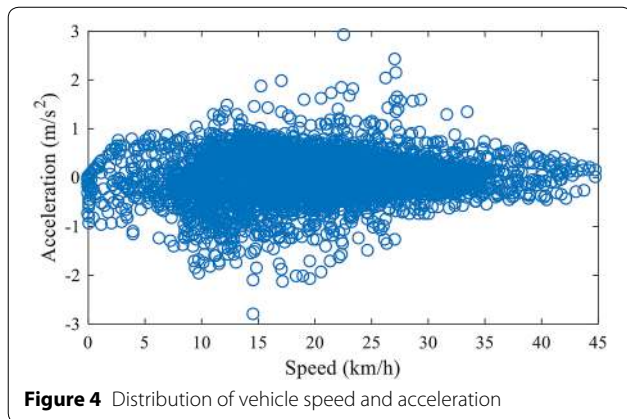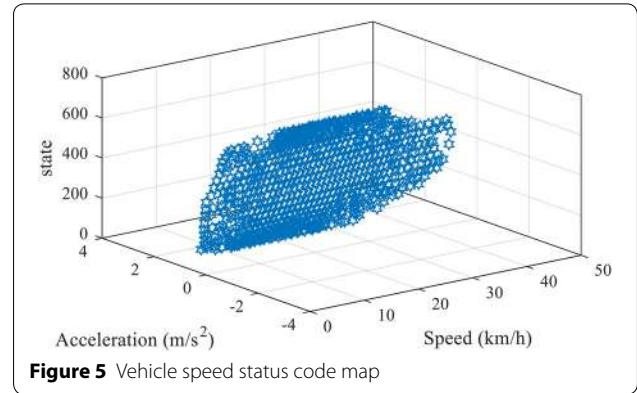**Figure 4** Distribution of vehicle speed and acceleration

Figure 5 Vehicle speed status code map

range is meshed. After obtaining the vehicle status grid, the grid without state points is removed. The remaining meshes are encoded as shown in Figure 5.

In the process of calculating the transition probability, because Markov's multi-step prediction leads to error accumulation and the prediction time of this paper is set to 5 s, the prediction time is relatively short, so the single-step Markov prediction technique is used to reduce the prediction error. Then, the state transition probability matrix of the road driving cycle is calculated according to the expression of the state transition probability, and the predicted steps are 1 s, 2 s, 3 s, 4 s, 5 s, respectively, as shown in Eq. (2):

$$P_{ij} = N_{ij} / N_i, \quad (2)$$

where N_{ij} is the number of state transitions from state i to state j; N_i represents the number of state transitions from state i to all states; P_{ij} represents the transition probability from state i to state j.

The predicted state S_1 is determined based on the current state S_0, and the state transition satisfies the condition shown as

$$\sum_{j=1}^{S_1-1} P_{S_0 j} < r < \sum_{j=1}^{S_1} P_{S_0 j}, \quad (3)$$

where r is a random number in the range 0–1. It can be seen from the inequality shown by Eq. (3), that when the state transition probability Ps_{0j} is large, the state j is more likely to be the prediction state.

According to the state transition probability calculated by Eq. (2) and satisfying the constraint characteristics of Eq. (3), an accurate Markov state transition matrix can be obtained. The state transition probability distribution is summarized in the next 5 prediction time intervals, as shown in Figure 6 , where the area size of the circle represents the transition probability of
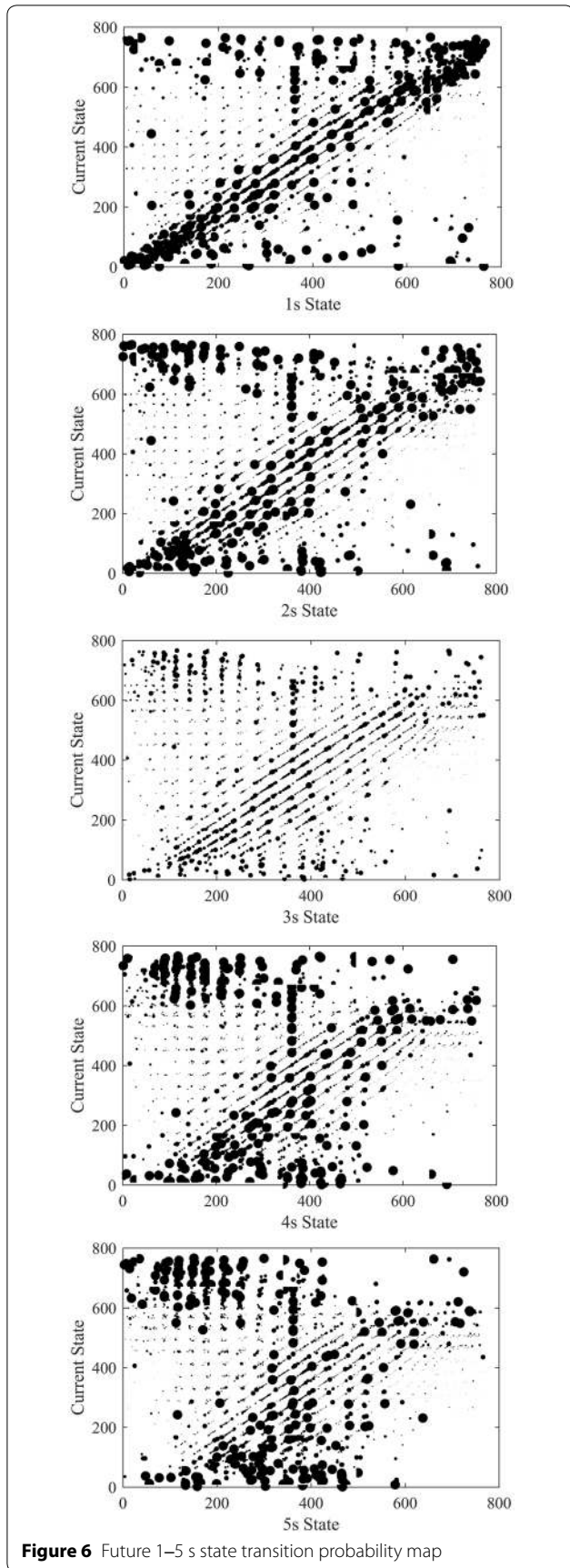
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Figure 6 Future 1–5 s state transition probability map

the state i to the next state j. The larger the area, the greater the transition probability.

In the final step of decision transfer and prediction, we can use the transition probability and current state of the future 1–5 s state transition matrix to complete Markov's future 1–5 s speed prediction, which is one of the prediction models used in the combined prediction algorithm of vehicle speed. The next prediction model used in the combined prediction algorithm of vehicle speed will be described later.

3.2 BP Neural Network Prediction Algorithm

BP neural network is a feed forward neural network based on error correction [32]. It generally has three or more layers of structure, including one or more input layers and an output layer; whereas, the neurons between the layers are fully correlated. There are no correlations between various neurons in the layer. The state vector $X = (x_1, x_2, \ldots, x_n)^{\mathrm{T}}$ is passed from the input layer to the hidden layer, and its output is calculated by Eq. (4). Where w_{ij} is the weight between the input layer and the hidden layer, a_j is the network hidden layer node threshold, and $f(\cdot)$ is the activation function. The hidden layer output H is passed to the output layer, and the state vector O of its output is calculated by Eq. (5). Where w_{jk} is the weight between the hidden layer and the output layer, and b_k is the network output layer node threshold. The error e is obtained by comparing the actual output with the expected output from Eq. (6).

$$H_j = f\left(\sum_{i=1}^{n} w_{ij}x_i - a_j\right), \ j = 1, 2, \ldots, l, \quad (4)$$
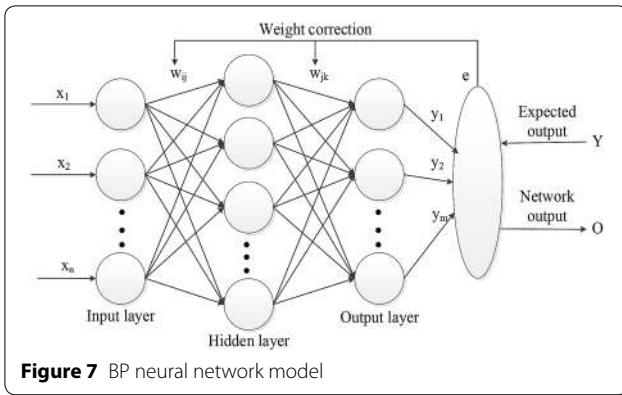
$$O_k = f\left(\sum_{j=1}^{l} H_j w_{jk} - b_k\right), \ k = 1, 2, \ldots, m, \quad (5)$$

$$e_k = Y_k - O_k, \ k = 1, 2, \ldots, m, \quad (6)$$

$$\begin{cases} w_{ij} = w_{ij} + \eta H_j\left(1 - H_j\right)x_i \sum_{k=1}^{m} w_{jk}e_k, \ i = 1, 2, \ldots, n; \ j = 1, 2, \ldots, l, \\ w_{jk} = w_{jk} + \eta H_j e_k, \ j = 1, 2, \ldots, l; \ k = 1, 2, \ldots, m, \end{cases} \quad (7)$$

$$\begin{cases} a_j = a_j + \eta H_j\left(1 - H_j\right)x_i \sum_{k=1}^{m} w_{jk}e_k, \ j = 1, 2, \ldots, l, \\ b_k = b_k + e_k, \ k = 1, 2, \ldots, m. \end{cases} \quad (8)$$

The error back-transfer reuses the weights and threshold updates layer-by-layer using Eqs. (7) and (8), where the learning rate η is expressed. This process is repeated

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Figure 7 BP neural network model

Table 1 BP neural network model parameters

Parameter name	Value or option
Hidden layer nodes	35
Hidden layer nodes transfer function type	Tansig
Output layer neuron excitation function	Purelin
Training function type	Trainlm
Learning function type	Trainrp
The max iteration number	20000
The network learning rate	0.05
Network training goal error	1×10^{-5}

until the error falls within an acceptable range. As shown in Figure 7, the established neural network model outputs the speed of the next 1–5 s.

By changing the network parameters, such as the number of neurons, the number of hidden layers, and the learning algorithm, the BP neural network model can obtain the network model that is most suitable for solving the problem [33]. To predict vehicle speed, it is necessary to adjust the input neuron types of the neural network model according to the range of vehicle speed fluctuation and the structure of the prediction model [34]. Appropriate input parameters for the predictive model can be obtained by correlation analysis or repeated testing. The selected parameters are meaningful for the differentiation of the vehicle's driving cycle. The combination of historical vehicle speed, average vehicle speed, idle time ratio, speed multiplied acceleration variance, speed variance, and positive acceleration mean can lead to a better prediction outcome.

The number of neurons and the number of layers in the hidden layer need to be selected within the appropriate range [35]. The hidden layer usually does not exceed two layers, and the BP neural network can realize the mapping from n-dimensional to l-dimensional. If the hidden layer neurons are too small, the convergence speed of the whole network may be lowered, and the convergence will not be easy to implement. Conversely, if there are too many neurons in the hidden layer, the network topology will be more complicated. The computational tasks will increase continuously during the iterative process, and the error may not be optimal [36]. Eq. (9) is two empirical formulas for estimating the number of hidden layer neurons:

$$\begin{cases} l = \sqrt{n+m} + a, \\ l = 2n + a, \end{cases} \tag{9}$$

where l is the number of the neurons in the hidden layer, n is the number of the neurons in the input layer, m is

the number of the neurons in the output layer, and a is a random number.

In fact, the method of determining the number of the hidden layer neurons based solely on the input and the output is inaccurate in many cases [37]. This is because the factors affecting the network structure are mainly the number of the training samples, the size of the sample noise, and the complexity of the function or classification problem to be simulated. Although the above method is lacking in accuracy in practical applications, we can use the above formula to determine the initial value of the hidden layer of the neural network. In most cases, it is still based on experimental methods used to gradually change the number of the hidden layer nodes. When the network error is the smallest, the optimal number of the hidden layer nodes is selected.

The three commonly used activation functions are shown in Eq. (10):

$$\begin{cases} y = f(x) = x, \\ y = f(x) = \dfrac{1}{1 + e^{-x}}, \ y \in (0, \ 1), \\ y = f(x) = \dfrac{1 - e^{-2x}}{1 + e^{-2x}}, \ y \in (-1, \ 1). \end{cases} \tag{10}$$

In the formula, the input range of x is real, and the three formulas are "purelin", "logsig", and "tansig". After the simulation tests, it is found that the hidden layer tends to use "logsig" and "tansig", while the output layer is more suitable for "purelin".

The learning algorithm has many types. There is no perfect theoretical guidance on the selection of training functions: it needs to be verified by practice. The result is that the elastic BP algorithm "trainrp" and the fixed-ratio variable gradient algorithm "trainscg" have better effects. In the training of the network, it is selected according to the actual situation. Finally, some parameters of the BP neural network model used in this paper are shown in Table 1.

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3.3 Combined Prediction Algorithm

Both of the above prediction models can predict the road driving cycle, but the accuracy of the single prediction model needs to be improved. It is an inefficient method for repeatedly debugging the parameters of a single prediction model on the way to pursue higher prediction accuracy. These two models have their own unique advantages, so the paper attempts to improve the prediction accuracy of the prediction model from the perspective of combined prediction. In the idea of combined prediction, the paper designs three combined methods of Markov and BP Neural Network (MBNN) to form combined prediction models. The three combinations of MBNN are described below.

The first combined prediction model, MBNN1, is shown in Figure 8. The road driving cycle V_MI is an input to the Markov prediction module, and the predicted 1–5 s vehicle speed of the Markov output is transmitted to the BP neural network module via the characteristic parameter extraction module of the vehicle speed. In this figure, the meaning of some variables has been expressed, the other parts, such as n and T, are the number of calculated vehicle speed, m is the number of calculated positive acceleration, v_i is the vehicle speed at time i, t_i is the duration of idle time, a_{i+} is the positive acceleration at time i, va_i is the product of velocity and acceleration at time i, and va_m is the product of the average velocity and the average

acceleration in n dimensions. At the same time, the BP module accepts the current vehicle speed V_current from the previous module and the future 1–5 s vehicle speed V_MO predicted by the Markov module. Finally, the BP neural network module outputs the future 1–5 s vehicle speed V_BO. The combination of the prediction model is mainly to use Markov to grasp the characteristics of the overall state of change and the high-accuracy local fitting of the BP neural network. The Markov model should first predict the change state of the future 1–5 s vehicle speed and then the BP neural network can fit this state with high precision.

The second combined prediction model, MBNN2, is shown in Figure 9. The method is similar to the first method. The main difference is that the BP network module increases the parameter of the historical approaching vehicle speed, called V_history.

The third combined prediction model MBNN3 is shown in Figure 10. The method is different from the first two methods, and the input of the vehicle speed characteristic parameter extraction module is a historical approaching vehicle speed. This type of parameter extraction method is the same one used in the BP neural network prediction model, except that the former has the input of Markov predicted vehicle speed. The main feature of the three MBNN combined prediction models is that the Markov predicted vehicle speed factor is added to the BP neural network prediction
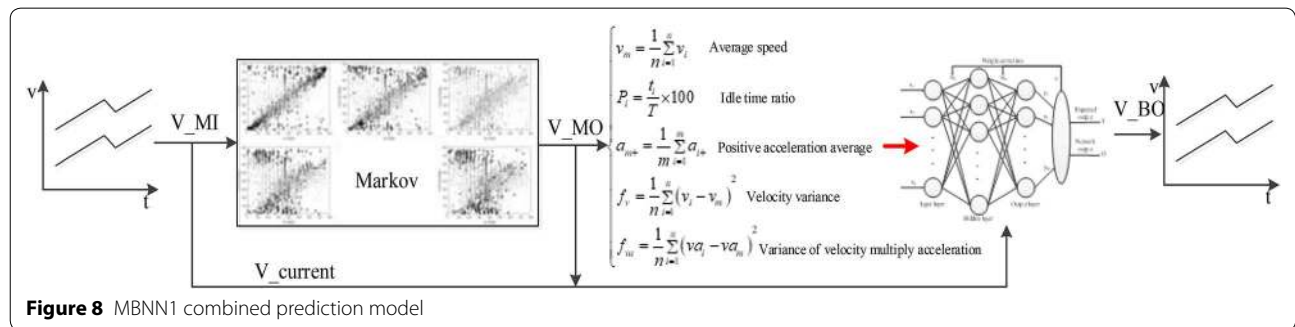

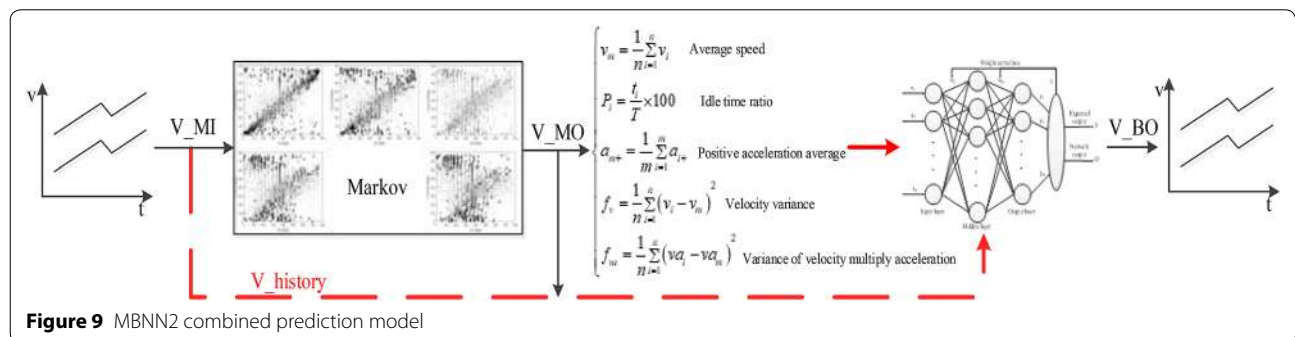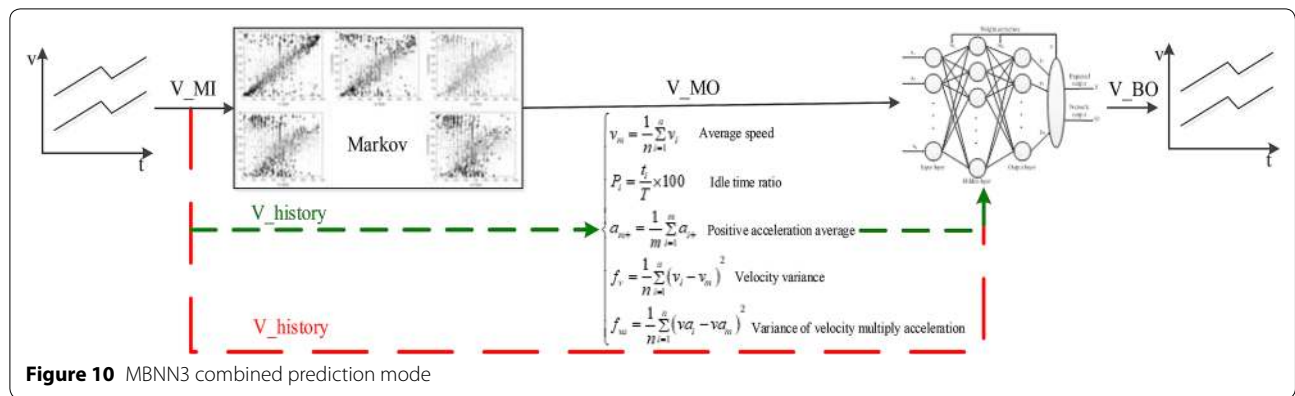**Figure 8** MBNN1 combined prediction model

Figure 9 MBNN2 combined prediction model

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Figure 10 MBNN3 combined prediction mode

module, and the final predicted vehicle speed is output by the BP neural network prediction module.

According to the combined prediction models proposed in this paper, the combined prediction flow chart is summarized in detail, as shown in Figure 11. The vehicle speed data sequence is divided into two parts: the former part is used as the training data of the Markov prediction model and the BP neural network model and the latter part is used as the comparison data of the test combined prediction model. The specific process of combination is divided into the following four steps.

> Step 1: Based on the training vehicle speed data, the Markov state transition matrix is calculated and the Markov speed prediction is performed.
> Step 2: The characteristic parameters of the Markov predicted vehicle speed is extracted. The red font in the figure is the characteristic parameters extraction of the historical near-vehicle speed used by MBNN3. The black font is the characteristic parameters extraction method used in MBNN1 and MBNN2.
> Step 3: BP neural network is trained according to the BP neural network input variable requirements of the three combined prediction models. From here, the training of the combined prediction model has been completed.
> Step 4: The prediction effect test of the combined prediction model is carried out. The other three sets of road driving cycles on the route is selected, and the Markov state transition matrix calculated in step 1 is used to obtain the Markov predicted vehicle speed for the future 1~5 s. Then, the characteristic parameters are extracted according to the combined prediction model requirements. Next, the BP neural network module input variables are imported to complete the prediction. At last, the contrast between the predicted vehicle speed and the actual vehicle speed is completed. The red font and line at

step 4 still indicate different methods of characteristic parameters extraction. The dotted line indicates the equivalent use of the functional module.
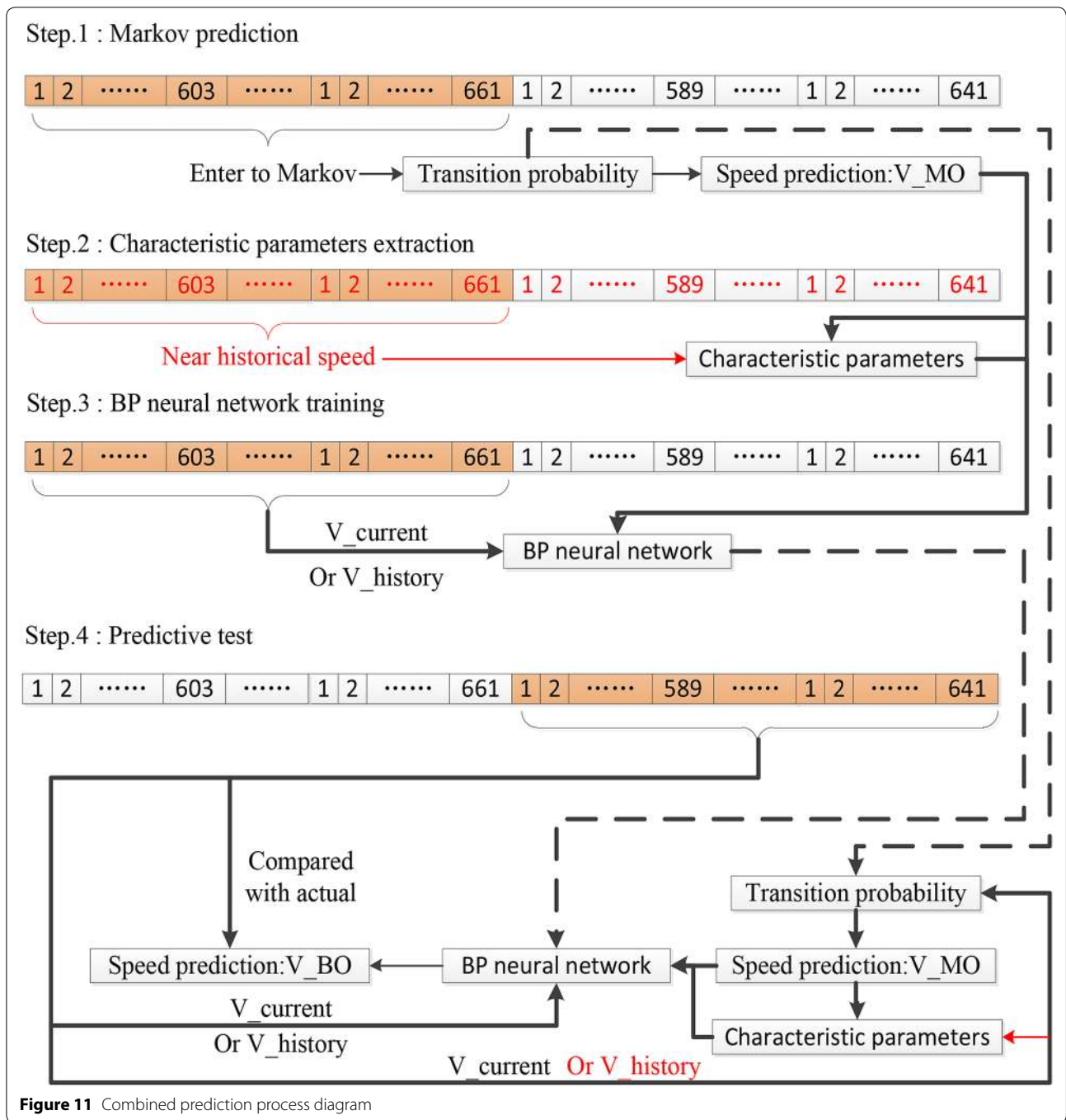
4 Prediction Results Analysis

The simulation analysis of this paper is based on the fixed route speed data and selects the other three sets of road driving cycles on the fixed route to verify the prediction effects of BP, Markov, MBNN1, MBNN2, and MBNN3. The following is a comparative analysis with a set of results data.

Figures 12 and 13 are the prediction effect diagrams of single prediction models. The initial 90 s is mainly influenced by the parameter of the historical vehicle speed, so the initial time of the prediction is selected at 89 s. In order to verify the prediction effect of the model, the speed prediction of the future 1–5 s is performed every second.

The final predicted speed curves overlap together with the actual vehicle speed curves to form the comparison figures of vehicle speed prediction. From these two figures, we can see the predicted characteristics of the Markov and BP neural network. The BP neural network has a slower response to the change state, but the local variation trend has a good fitting effect. It is often fitted to the trend of the speed of the next few seconds, but there is no actual follow-up to the actual speed curve. Therefore, the speed predicted by the BP neural network in Figure 13 is mostly attached to the surface of the actual speed curve. On the contrary, in Figure 12 Markov better follows the global speed change state. Most of the predicted vehicle speeds can coincide with the actual vehicle speed curve, but the local variation trend fitting effect is poor, resulting in large error.

The initial conditions of MBNN are the same as for a single prediction model. Figures 14, 15 and 16 are the diagrams showing the speed prediction effects of the

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Figure 11 Combined prediction process diagram

three MBNNs. It can be seen from the figure that MBNN better combines the advantages of the Markov model and BP neural network model. The predicted speed curve better follows the change state of the actual speed curve, and can overlap better than the BP neural network speed prediction. Furthermore, the fluctuation of the locally fitted speed curve is smaller than that of the Markov prediction.

In order to see the above predicted performance more clearly, these images are partially enlarged, as shown in Figure 17. The results are consistent with the characteristics of the single prediction model analyzed above. The results of the neural network perform well linearly, while Markov fluctuates greatly. The use of the combination method balances the predicted performance of the two models and the predicted performance is better.
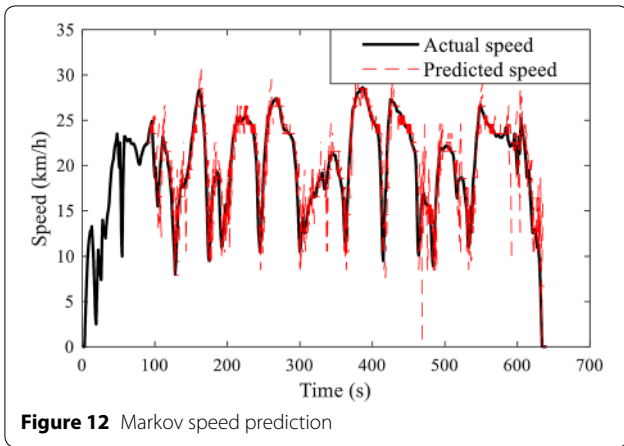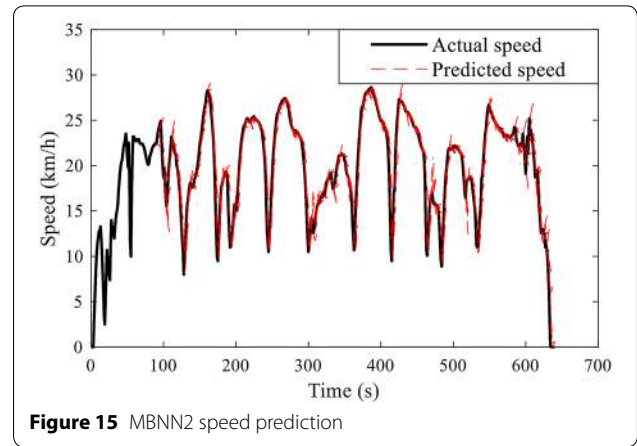
Figure 12 Markov speed prediction
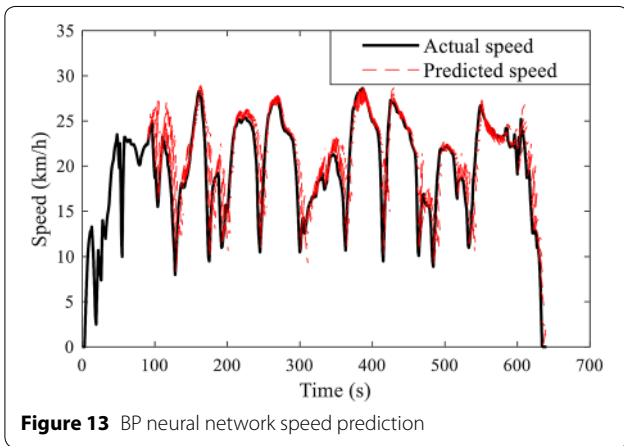

Figure 15 MBNN2 speed prediction

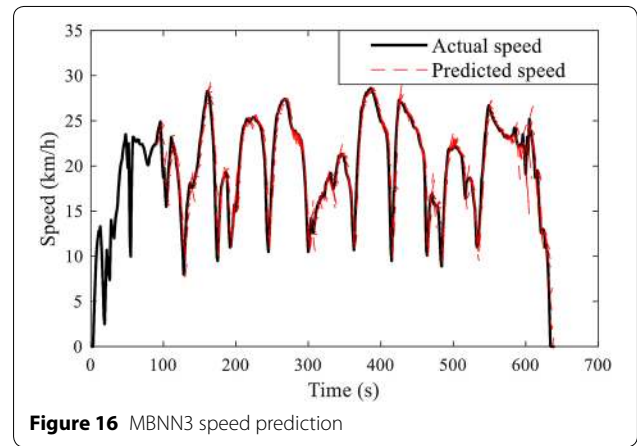**Figure 13** BP neural network speed prediction

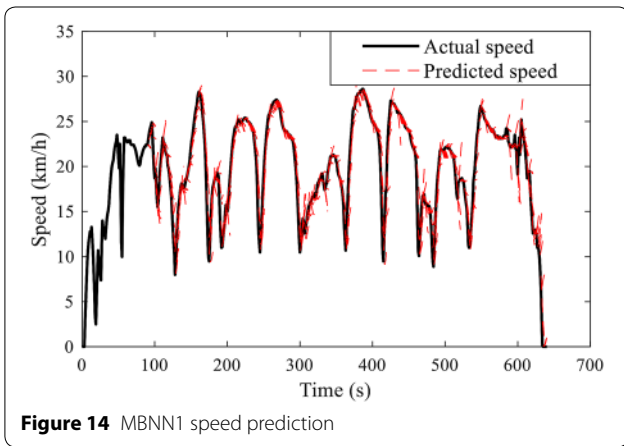**Figure 16** MBNN3 speed prediction

Figure 14 MBNN1 speed prediction

Intuitively, the predictions of the three MBNN are not very different. The following analysis is based on the data.

Figure 18 compares the vehicle speed prediction errors of the five prediction algorithm models. The prediction error is calculated from the mean of the prediction bias within the 5 s prediction duration recorded every second. As can be seen from the figure, MBNN can reduce the fluctuation range of error compared to a single prediction model. At the moments of large error, the prediction error of MBNN is smaller than that of a single prediction model, and other times can be kept at an average level.

The paper uses Root Mean Square Error (RMSE) to further evaluate the accuracy of speed prediction [38]. The expression of RMSE is as shown in Eq. (11), and the evaluation time of RMSE can be adjusted by changing the value of n:

$$\mathrm{RMSE} = \sqrt{\frac{\sum\limits_{i=1}^{n}\left(v_{p,i} - v_{r,i}\right)^2}{n}}, \tag{11}$$

where $v_{p,i}$ is the predicted speed of the i seconds after time p, $v_{r,i}$ is the actual speed of the i seconds after time r, time r, and time p are the same time point. In order to distinguish between predicted and actual values, different symbols are used: n represents the RMSE evaluation steps.
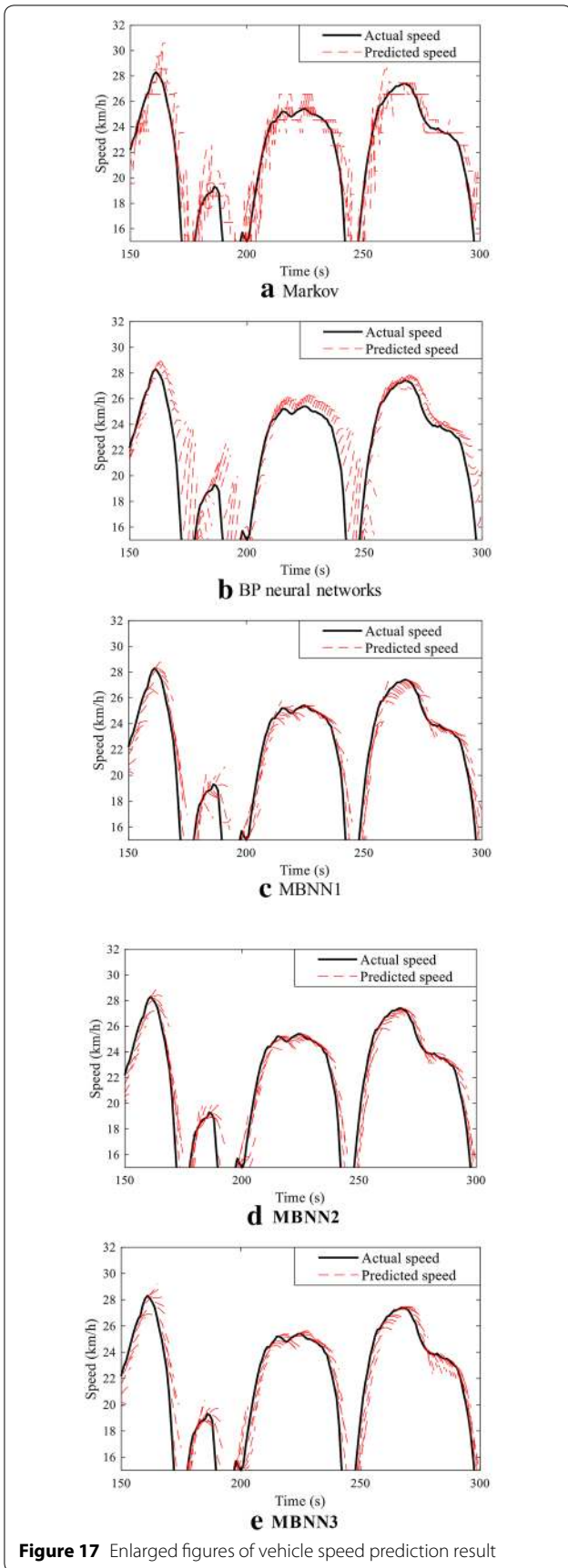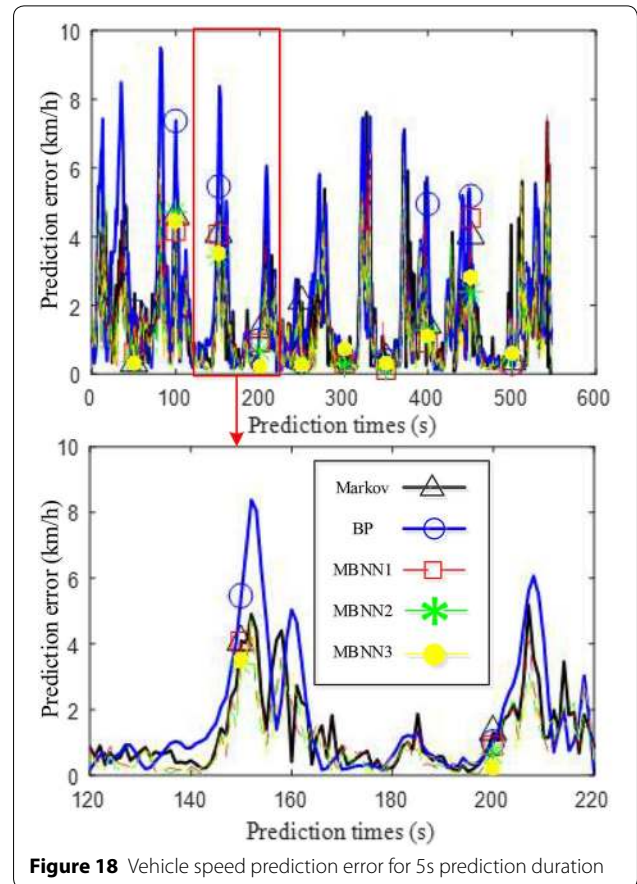
Figure 18 Vehicle speed prediction error for 5s prediction duration

The vehicle speed prediction evaluation results obtained by Eq. (11) are listed in Table 2, which summarizes the prediction accuracy of the five prediction models in the fixed route and the three groups of 5 s within the vehicle speed prediction simulation. Taking the first set of predictions as an example, the RMSE in a single BP prediction model and a Markov prediction model within 5 s is 2.3775 m/s and 2.2123 m/s, while the RMSE performances in the three MBNN combined prediction models within 5 s are 1.7880 m/s, 1.5420 m/s, and 1.5366 m/s, respectively. Compared to the better performing Markov prediction model, the improvement ratios of the combined prediction models are about 19%, 30%, and 31%, respectively. Furthermore, in the other two groups of speed prediction, the improvement ratios are 17%, 26%, 27% and 20%, 28%, and 28%. On the whole, the performance improvement ratios of the three combined prediction algorithms are 19%, 28%, and 29%. Among them, MBNN2 and MBNN3 performed better, and MBNN3 performed best in most cases. Summarizing the performance of the combined prediction algorithms, the MBNN prediction models can improve the accuracy by 25.3% on average. Furthermore, it can be seen from the law of Table 2 that within a small prediction step,

Figure 17 Enlarged figures of vehicle speed prediction result

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Table 2 The RMSE assessment of the five prediction models (m/s)

RMSE		BP	Markov	MBNN1	MBNN2	MBNN3
Speed 1	1 s	0.7749	0.6360	0.6988	0.6449	0.6513
	2 s	1.2176	1.0069	1.0007	0.8880	0.9096
	3 s	1.6094	1.3927	1.2758	1.1093	1.1287
	4 s	1.9981	1.8147	1.5356	1.3260	1.3337
	5 s	**2.3775**	**2.2123**	**1.7880**	**1.5420**	**1.5366**
Speed 2	1 s	0.8198	0.6989	0.6939	0.6680	0.6524
	2 s	1.3068	1.0152	0.9849	0.9068	0.8888
	3 s	1.7284	1.3613	1.2417	1.1173	1.0913
	4 s	2.1424	1.7272	1.4735	1.3196	1.2920
	5 s	**2.5346**	**2.0335**	**1.6884**	**1.5132**	**1.4851**
Speed 3	1 s	0.6961	0.6330	0.6116	0.5758	0.5872
	2 s	1.0943	0.9044	0.8626	0.7863	0.7979
	3 s	1.4581	1.2219	1.0866	0.9743	0.9884
	4 s	1.8283	1.5621	1.3005	1.1610	1.1769
	5 s	**2.1861**	**1.8848**	**1.5055**	**1.3450**	**1.3593**

the accuracy of the prediction model is not much different because the prediction accuracy is high. However, as the prediction step length is extended, the accuracy advantage of MBNN will become larger and larger.

5 Conclusions

In order to improve the energy management effect of plug-in hybrid vehicles, this paper studies the problem of vehicle speed prediction in the control strategy. An experiment on a fixed route was conducted and a set of road driving cycle extraction methods were designed. The BP neural network and Markov prediction model were adopted and analyzed. Although the speed prediction of the fixed route can be realized by a single prediction model, the prediction accuracy of a single prediction model reaches a certain range; therefore, it is difficult to obtain an improvement in prediction effect by only debugging a single prediction model. Better speed prediction accuracy has an impact on the energy management effect of plug-in hybrid vehicles. Therefore, this paper proposes a combined prediction algorithm that can efficiently improve prediction accuracy. Based on the advantages of a BP neural network and Markov prediction algorithm, the prediction model is improved, and three combined prediction models, MBNN1, MBNN2, and MBNN3, are designed. The prediction results show that the predicted speed curves obtained by the three MBNN models follow the change state of the actual speed curve better, and the fluctuation of the prediction error is reduced. Finally, the predictive value of MBNN is evaluated via RMSE from the perspective of generalization ability and accuracy. The RMSE performance in 5 s is distributed between

1–2 m/s. Compared with the preferred single prediction model adopted in this paper, the MBNN prediction models can improve accuracy by 25.3% on an average. This proves that the MBNN prediction models have obvious advantages. In summary, the designed combined prediction model can give full play to the prediction advantages of a Markov and BP neural network, which will play an important role in speed prediction and energy optimization of plug-in hybrid vehicles.

Authors' contributions
LZ was in charge of the whole trial; WL wrote the manuscript; BQ assisted with sampling and laboratory analyses. All authors read and approved the final manuscript.

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Competing interests
The authors declare no competing financial interests.

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