Advances in Engineering Innovation Vol.17 Issue 4 EWA Publishing
Available Online: 26 March 2026 DOI: 10.54254/2977-3903/2026.32449

Research on electric vehicle energy consumption prediction based on BP neural network

Ruizhe Ding**, *Junzhe Zhao

Beihang University, Beijing, China

*Corresponding Author. Email: dingruizhe@buaa.edu.cn

Abstract. With the rapid growth of society's technology and economy, the energy and pollution problems brought by motor vehicles are gradually exposed to people. At this time, electric vehicles seem to be a good solution. However, due to the limited number of charging piles, long charging time and inadequate supporting facilities, people may feel uneasy about the range of electric vehicles. Accurately obtaining the range of a vehicle can effectively alleviate this "range anxiety". To obtain the accurate range, we need to predict the energy consumption on the planning path. In this paper, we build a two-level energy consumption prediction model based on the speed characteristics as a bridge to obtain accurate energy consumption prediction for electric vehicles. Firstly, using the experimentally obtained road traffic information and *v-t* data, the road and traffic characteristics parameters, vehicle speed characteristics parameters and energy consumption of each segment within the segment are calculated, and the characteristics parameters suitable as intermediaries of the secondary energy consumption prediction model are selected from the vehicle speed characteristics parameters. Secondly, the BP neural network for energy consumption prediction is established with the vehicle speed characteristic parameter as the input quantity and the energy consumption as the output quantity; the BP neural network for vehicle speed characteristic parameter prediction is established with the road and traffic characteristic number as the input quantity and the vehicle speed characteristic parameter as the output quantity. Lastly, the sequences of road and traffic feature parameters are extracted from the experimental data and input into the secondary energy consumption prediction model to obtain the predicted energy consumption and compare it with the actual energy consumption. The verification shows that the secondary energy consumption prediction model has a high accuracy.

Keywords: BP neural network, electric vehicle, long-time energy consumption prediction

1. Introduction

1.1. Research background and significance

With the rapid development of economy and society, the problems caused by motor vehicles have become the focus of public attention. Under the dual pressures of energy shortage and environmental pollution, people have shifted their attention to new energy vehicles. Although people's interest in electric vehicles is growing day by day, their limited driving range has always been a major concern for consumers. A better understanding of energy consumption and the ability to accurately predict the remaining battery energy along the upcoming route can effectively reduce such anxiety. However, the energy consumption prediction of electric vehicles remains a pressing challenge to be addressed. Therefore, accurate and effective prediction of electric vehicle energy consumption is of great significance for improving the performance and popularization rate of electric vehicles.

The energy consumption of electric vehicles is affected by numerous factors. Different driving behaviors of drivers will lead to different driving states of the vehicle; drivers have distinct driving characteristics and may show different driving tendencies even in similar scenarios. In addition, the vehicle's own structural parameters and environmental factors also exert an influence on the energy consumption of electric vehicles. As a typical nonlinear system, electric vehicles have the disadvantages of large calculation load and complex model structure if theoretical modeling methods are adopted, which makes such methods unsuitable for real-time identification. At present, scholars at home and abroad mainly start from a data-driven perspective to analyze the correlation between various operating parameters and driving energy consumption, so as to simplify the system model as much as possible while ensuring the prediction accuracy.

1.2. Research status

Research on electric vehicle energy consumption initially started from the construction of monitoring systems, energy consumption modeling, and analysis of influencing factors. Existing studies have constructed an electric vehicle energy consumption monitoring system integrating electric energy metering, position monitoring and wireless data transmission, which provides a technical foundation for vehicle operation data collection and energy consumption evaluation [1]. Aiming at the relationship between vehicle kinematic parameters and energy consumption, relevant studies have established prediction models with different input levels using the multiple linear regression method, and compared the impacts of variables such as travel distance, driving time, temperature, acceleration and original kinematic data on the prediction effect [2]. Meanwhile, some studies have carried out joint prediction of speed profiles and energy consumption by combining real-time traffic data, driving styles and on-board information systems, and further analyzed the uncertainty of model prediction and parameter sensitivity [3]. For unfamiliar road scenarios, existing research has realized route energy consumption estimation using map data and vehicle parameters [4]. In terms of influencing factors, studies have shown that driving behavior, vehicle speed, acceleration, road gradient and other factors all have a significant impact on the energy consumption of electric vehicles [5]. In addition, studies have pointed out that external environmental conditions such as wind speed, road gradient and ambient temperature also have an obvious influence on the energy consumption and driving range of electric vehicles [6, 7].

In recent years, research on electric vehicle energy consumption prediction has further developed towards the directions of data-driven methods and deep learning. Existing studies have established machine learning models based on real operation data, and improved the accuracy of energy consumption prediction by using multi-dimensional features such as vehicle speed, road gradient and environmental conditions [8]. In terms of deep learning methods, some studies have combined the Long Short-Term Memory (LSTM) network with the Transformer structure to mine the time series features and long-term dependencies in vehicle operation data, thus improving the performance of energy consumption prediction [9]. Aiming at the problem of large data distribution differences between different vehicles, relevant studies have begun to introduce pre-trained models and transfer learning-based modeling ideas to enhance the generalization ability of models under multi-vehicle and multi-scenario conditions [10]. In addition, methods such as ensemble learning, multi-model fusion and physics-informed neural networks have also been gradually applied to the research of electric vehicle energy consumption prediction, which improve the prediction accuracy while enhancing the stability and interpretability of the models [11, 12].

1.3. Main work of this paper

Aiming at the electric vehicle energy consumption prediction based on planned routes, this paper establishes a two-level energy consumption prediction model. The road traffic characteristic parameters, vehicle speed characteristic parameters and segmented energy consumption of the experimental road sections are calculated. Appropriate vehicle speed characteristic parameters are selected to construct a two-level energy consumption prediction model consisting of a vehicle speed characteristic parameter prediction model and a driving energy consumption prediction model based on vehicle speed characteristics. Finally, the prediction error of energy consumption is analyzed.

2. Data processing for energy consumption prediction

At present, there are two main types of driving energy consumption prediction: one is short-term prediction, which predicts the short-term driving energy consumption demand based on the vehicle's current speed; the other is long-term prediction, which predicts the total driving energy demand of the entire planned driving route. The research objective of this paper is to realize long-term prediction, that is, to predict the driving energy demand along the entire planned route before the trip, which is characterized by on-line and long-time properties. For long-term prediction, the driving cycle prediction method considering real-time road traffic conditions is more suitable. Among them, the most intuitive method is energy consumption prediction based on speed prediction, which can predict the average speed level and change trend of different road sections at a macro level, but is not sensitive to the dynamic characteristics of vehicle driving, resulting in low prediction accuracy of driving energy consumption.

There are two main implementation methods for long-term energy consumption prediction, as shown in Figure 1. Considering the limitations of driving energy consumption prediction based on vehicle speed characteristics or driving condition characteristics, this paper conducts driving energy consumption prediction based on the vehicle speed characteristic parameters of the future planned route instead of the predicted speed sequence. A two-level energy consumption prediction model is constructed by using the BP neural network, with the ultimate goal of realizing the long-term prediction of the energy demand at the vehicle wheel end. Based on the real-time road and traffic information of the planned route provided by the vehicle navigation system, the long-time vehicle speed characteristic prediction neural network model is used to predict the sequence of road segment speed characteristic parameters of the vehicle driving on the planned route under various working conditions. The predicted sequence of vehicle speed characteristic parameters is input into the driving energy consumption model based on vehicle speed characteristics, and the corresponding sequence of driving energy consumption of road segments can be finally predicted. The total driving energy consumption demand of the corresponding road is calculated by summing up the sequence of driving energy consumption values of each segment.

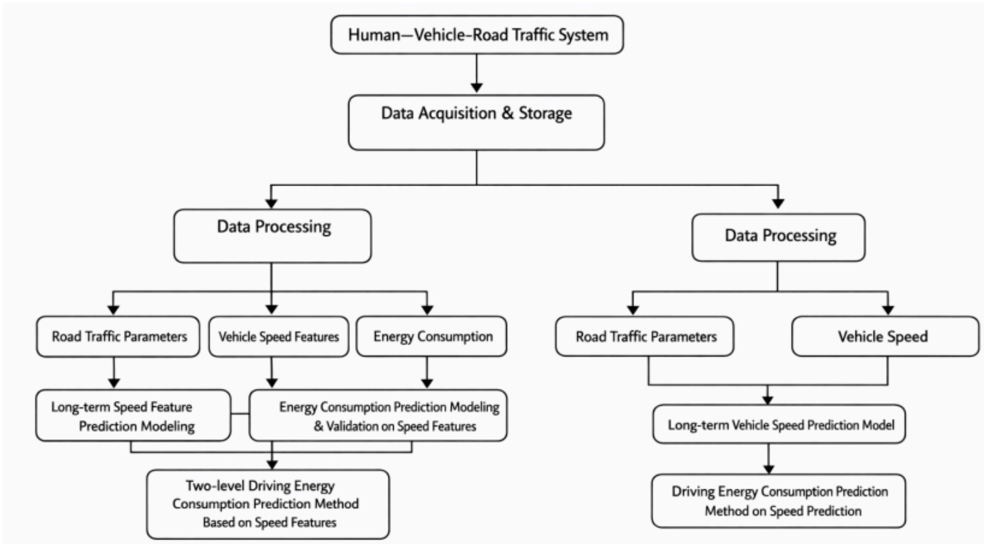


Figure 1. Two methods for long-term energy consumption prediction

2.1. Data acquisition

In this study, an experimental dataset for driving energy consumption prediction is constructed based on real vehicle tests, in which drivers drive the test vehicle to complete actual road driving tests on the typical road network in Nanjing. The traffic environment and road network data are obtained from the Amap Web Service Application Programming Interface (API) interface and third-party traffic APPs, including Geographic Information System (GIS) geographic information and traffic flow state parameters (including road type, road speed limit, traffic congestion degree, etc.). The vehicle driving data are collected in real time through the on-board CAN bus and sensors, recording key indicators such as time t, real-time vehicle speed v, and single trajectory driving distance dis. The data cover three basic road types: urban roads, suburban roads and expressway viaducts. A total of 50 driving tests are completed on the selected routes, forming a complete sample of real vehicle driving data under multiple scenarios.

Since the specific speed and driving time vary in each test, it is not feasible to establish a regression model with time as the independent variable. However, the driving distance of each single trip is fixed, so the driving distance of a single trip is considered as the independent variable. As the *v-t* data are collected in the experiment, the *v-t* data are converted into *v-dis* data using the following formula:

$$\frac{v_{t+1}-v_t}{dis_{t+1}-dis_t} = \frac{v-v_t}{dis-dis_t} \tag{1}$$

where $dis_{t+1} - dis_t = 1$ is satisfied.

2.2. Acquisition of road and traffic characteristic parameters

To increase the number of training sets of the energy consumption prediction model and thus improve its prediction accuracy, the experimental road sections are divided into equal segments, and a set of characteristic parameters is extracted from the sequence data of each segment as a sample. The prediction window length is set to 50 meters, and the driving road is divided into a series of road segments with the same length, then the road and traffic characteristic parameter data of each segment are obtained. For the road, traffic and other characteristic parameters within each segment, since each point in the segment has a set of characteristic parameters, the average value of these parameters is taken as the road and traffic characteristic parameters of the segment.

2.3. Calculation of segmented energy consumption

Based on the vehicle driving energy balance equation, the vehicle's driving demand power can be calculated from the consumption side, and the consumed energy can be obtained by multiplying the power by the time taken to pass the segmented distance and accumulating the results.

$$P_e = \frac{mgfu_a}{3600} + \frac{mgau_a}{3600} + \frac{C_d A u_a}{76140} + \frac{m\delta}{3600}\frac{du}{dt} \tag{2}$$

$$E = \sum_{i=1}^{n} P_e \cdot t_i \tag{3}$$

Where: P_e is the driving demand power; m is the total vehicle mass; g is the gravitational acceleration; u_a is the vehicle speed; a is the road gradient; f is the rolling resistance coefficient; A is the windward area; C_d is the air resistance coefficient; δ is the rotational mass conversion coefficient; $\frac{du}{dt}$ is the linear acceleration; E is the required energy consumption. The relevant parameters of the test vehicle are shown in Table 1.

Table 1. Relevant parameters of the test vehicle

Parameter	Value	Unit
m	1,580	kg
g	9.8	m/s^2
A	1.8	m^2
f	0.015	-
C_d	0.3	-
δ	1.1	-

In the research process, the test route is basically a horizontal road with no obvious height difference, so the energy consumption caused by the horizontal height difference is set to 0 in the model establishment. Therefore, the formula can be simplified as:

$$P_e = \frac{mgfu_a}{3600} + \frac{C_d A u_a}{76140} + \frac{\delta m u_a}{3600}\frac{du}{dt} \tag{4}$$

Since *v-dis* data are adopted in this paper, the idle energy consumption generated when the vehicle speed is 0 due to the driver's personal needs or traffic conditions is not included in the calculation and is set to 0. In fact, such energy consumption varies with the fuel consumption characteristics of different engines at idle speed, but as mentioned earlier, this paper predicts the demand energy at the vehicle wheel end.

2.4. Acquisition of vehicle speed characteristic parameters

For different position intervals of the entire planned driving route, the road characteristics and traffic states are different and changeable. It can be considered that for a definite human-vehicle system, the vehicle speed characteristic parameters are mainly determined by road characteristics and traffic states, and the vehicle speed characteristic parameters have a strong correlation with energy consumption.

Firstly, the acceleration sequence is obtained by processing the speed sequence data using the uniform acceleration formula:

$$a_i = \frac{v_i^2 - v_{i-1}^2}{2 \times 3.6^2} \tag{5}$$

Vehicle speed characteristic parameters refer to the parameters reflecting the characteristics of driving cycles, which are extracted and calculated from the speed sequence. For the selection of vehicle speed characteristic parameters, relevant literatures generally define about 10 to 15 characteristic parameters [13]. With reference to various literatures, 14 basic characteristic parameters are initially selected in this paper: average speed v_{me}, average acceleration a_{me2}, average positive acceleration a_{me1}, average negative acceleration a_{me2}, speed variance σ_v, acceleration variance σ_a, speed-acceleration (inertial energy) variance σ_{va}, acceleration proportion P_a, deceleration proportion P_d, constant speed proportion P_c, maximum acceleration a_{max}, minimum acceleration a_{min}, maximum speed-acceleration va_{max}, minimum speed-acceleration va_{min}. The definitions of the above characteristic parameters are as follows:

Average speed v_{me}: The average value of vehicle speed over the sampling length

$$v_{me} = \frac{\sum_{i=1}^{n} v_i}{n} \tag{6}$$

Average acceleration a_{me}: The average value of acceleration over the sampling length

$$a_{me} = \frac{\sum_{i=1}^{n} a_i}{n} \tag{7}$$

Average positive acceleration a_{me1}: The average value of positive acceleration over the sampling length

$$a_{me1} = \frac{\sum_{k=1}^{p} a_j}{m} \tag{8}$$

Average negative acceleration a_{me2}: The average value of negative acceleration over the sampling length

$$a_{me2} = \frac{\sum_{k=1}^{p} a_k}{n} \tag{9}$$

Speed variance σ_v: The variance of speed over the sampling length

$$\sigma_a = \sqrt{\frac{\sum_{i=1}^{n} (a_i - a_{me})^2}{n}} \tag{10}$$

Acceleration variance σ_a: The variance of acceleration over the sampling length

$$\sigma_a = \sqrt{\frac{\sum_{i=1}^{n} (a_i - a_{me})^2}{n}} \tag{11}$$

Speed-acceleration variance σ_{va}: The variance of speed-acceleration over the sampling length

$$\sigma_{va} = \sqrt{\frac{\sum_{i=1}^{n} (va_i - va_{me})^2}{n}} \tag{12}$$

Acceleration proportion P_a: The percentage of acceleration distance in the sampling length

$$P_a = \frac{S_a}{S} \times 100\% \tag{13}$$

Deceleration proportion P_d: The percentage of deceleration distance in the sampling length

$$P_d = \frac{S_i}{S} \times 100\% \tag{14}$$

Constant speed proportion P_c: The percentage of constant speed distance in the sampling length

$$P_c = \frac{S_c}{S} \times 100\% \tag{15}$$

Maximum acceleration a_{max}: The maximum acceleration over the sampling length

$$a_{max} = \{a_1, a_2, a_3 \ldots\ldots a_n\}_{max} \tag{16}$$

Minimum acceleration a_{min}: The minimum acceleration over the sampling length

$$a_{min} = \{a_1, a_2, a_3 \ldots\ldots a_n\}_{min} \tag{17}$$

Maximum speed-acceleration va_{max}: The maximum speed-acceleration over the sampling length

$$va_{max} = \{va_1, va_2, va_3 \ldots\ldots va_n\}_{max} \tag{18}$$

Minimum speed-acceleration va_{min}: The minimum speed-acceleration over the sampling length

$$va_{min} = \{va_1, va_2, va_3 \ldots\ldots va_n\}_{max} \tag{19}$$

2.5. Selection of characteristic parameters

Although 14 characteristic parameters are mentioned in the previous section, each parameter has a different impact on energy consumption. If all the obtained characteristic parameters are used for the subsequent neural network modeling, the complexity of the neural network will be greatly increased, the calculation time will be significantly prolonged, and some characteristic parameters may have a strong correlation, resulting in information overlap and redundancy. Therefore, the correlation coefficient is used to evaluate the degree of influence of vehicle speed characteristic parameters on energy consumption and the linear correlation degree between characteristic parameters. Based on the comprehensive analysis of the two aspects, only part of the characteristic parameters are selected for the subsequent energy consumption modeling. Thus, the correlation coefficient is used for measurement in this paper [14]:

Pearson correlation coefficient: It measures the correlation coefficient between two continuous random variables.

Spearman correlation coefficient: It is a rank correlation coefficient solved according to the rank order of original data, also known as the Pearson correlation coefficient between rank variables.

The above two coefficients reflect the direction and degree of the change trend between two variables, with a value range of [-1, 1]. A value close to 1 indicates a strong positive correlation. Verified by the normality test function lillietest, none of the 14 driving cycle characteristic parameters meet the normal distribution conditions, so the Spearman correlation coefficient is used for correlation analysis. The correlation analysis function corrcoef is used to conduct correlation analysis on the 14 characteristic parameters and energy consumption, and the correlation coefficient matrix of the 14 characteristic parameters and energy under various working conditions is obtained, which is a symmetric matrix. Several characteristic parameters with large correlation coefficients are selected, and it is ensured that the extracted data have no correlation to avoid linear redundancy. Referring to literature [15] for the definition of correlation between two sets of data, this paper holds that two variables are correlated when the absolute value of the correlation coefficient is greater than or equal to 0.8. The finally selected characteristic parameters are shown in Table 2.

Table 2. Selected characteristic parameters

Road Condition	Selected Characteristic Parameter		
Urban	va_{max}	P_a	a_{me}
Suburban 1	va_{max}	P_a	a_{me}
Suburban 2	P_a	va_{max}	a_{me}
Expressway	a_{me}	va_{max}	a_{max}

2.6. Summary of this chapter

To sum up, this chapter introduces two ideas for long-term energy consumption prediction and decides to adopt the energy consumption prediction idea based on long-time vehicle speed characteristic prediction, i.e., the two-level energy consumption prediction model, and also introduces the acquisition method of the data used in this paper. The road characteristic parameters collected are processed by taking the average value by segments to obtain the sequence of road characteristic parameters under various road conditions.

The segmented energy consumption and the vehicle speed characteristic parameters of each segment are calculated from the collected speed sequence, and the Spearman correlation coefficient is used for correlation analysis to select the vehicle speed characteristic parameters serving as the link of the two-level energy consumption prediction model under each road condition.

The finally established sample dataset includes road traffic characteristic parameters, selected vehicle speed characteristic parameters and segmented energy consumption.

3. Two-level energy consumption prediction model

This chapter establishes a two-level energy consumption prediction model. The first-level model takes road and traffic characteristic parameters as input and outputs vehicle speed characteristic parameters; the second-level model takes vehicle speed characteristic parameters as input and outputs segmented energy consumption. After a planned route is given, the road traffic characteristic parameters of the planned route are obtained from the navigation system, and the total predicted energy consumption of the entire planned route can be obtained from the two-level energy consumption prediction model.

3.1. Principle of BP neural network

The Back Propagation (BP) Neural Network was proposed by scientists such as Rumelhart and McClelland in 1986, which is a multi-layer feedforward neural network trained by the error back propagation algorithm. The BP neural network is composed of an input layer, a hidden layer and an output layer, and is used to process data with nonlinear relationships. The hidden layer can have one or more layers, and each layer can have several neurons. Figure 2 shows the schematic diagram of a single neuron model, and Figure 3 shows the schematic diagram of a neural network model. The connection between nodes of different layers is represented by weights. The error between the actual output and the ideal output under a specific input is calculated, and the threshold and connection weights in the neural network are derived by using the "chain rule". The gradient descent algorithm is adopted to approach the minimum value until the set conditions are met [16].

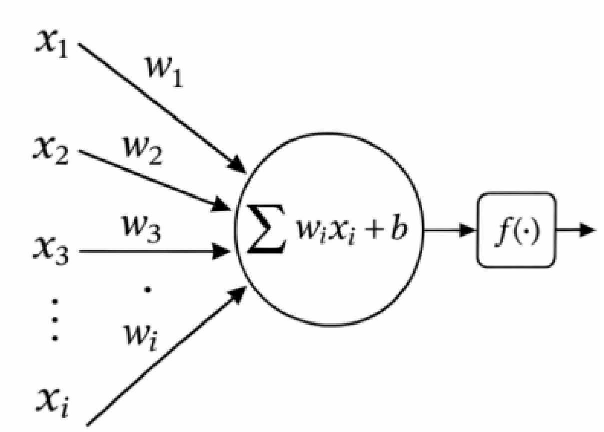


Figure 2. Single neuron model

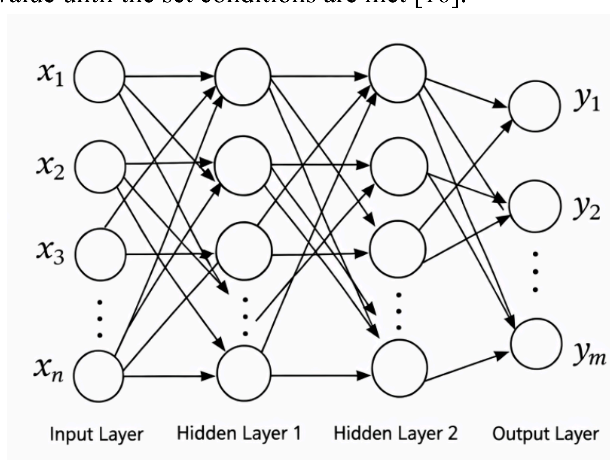


Figure 3. Neural network model

Normalization refers to processing each row of the matrix to the interval [-1,1] or [0,1], and the neural network uses the values obtained after normalization as input and output. Without normalization, the input and weights will be polarized, resulting in numerical problems. Normalization can avoid such problems to a certain extent and accelerate the convergence of the training network, making the neural network obtain prediction results faster, though it is not a mandatory step. The mapminmax function is adopted in this paper:

$$y = \frac{x - xmin}{xmax - xmin} \tag{20}$$

The minimum and maximum values of each row of the matrix are mapped to 0 and 1. The predicted values obtained when the neural network performs prediction need to be denormalized.

In some cases, a single hidden layer BP neural network has a better effect than a double hidden layer structure, and using fewer hidden layers can greatly reduce the training time. However, in other cases, a double hidden layer BP neural network can achieve a better fitting effect. In this paper, both the vehicle speed characteristic parameter prediction neural network and the energy consumption prediction neural network adopt a double hidden layer structure.

At present, there is no systematic method to determine the number of neurons in the hidden layer of an artificial neural network, which is usually determined by the experience and estimation of the neural network designer in actual operation, or by trial calculation and comparison. However, the upper and lower bounds of the number of neurons can be obtained from some literatures.

A commonly used empirical formula to determine the number of neurons in the hidden layer is [17]:

$$N_{hid} = \sqrt{N_{in} + N_{out}} + a \tag{21}$$

Where: N_{in} is the number of neurons in the input layer, N_{out} is the number of neurons in the output layer, N_{hid} is the number of neurons in the hidden layer, and $1 \leq a \leq 10$.

There are also some other methods for determining the number of neurons [18]:

$$N_{hid} \leq N_{train}/[R + (N_{in} + N_{out})] \tag{22}$$

Where: N_{train} is the number of training samples, and R is a constant with $5 \leq R \leq 10$.

Some literatures hold that the range of the hidden layer should be as follows [19]:

$$\frac{N}{N_{out}} \leq N_{hid} \leq \left(\frac{N}{N_{out}}\right) * log_2^{N/N_{out}} \tag{23}$$

3.2. Energy consumption prediction network

Due to the large differences in road traffic characteristic parameters, vehicle speed characteristic parameters and energy consumption under various working conditions, a unified model may lead to a large error. Therefore, modeling and analysis are carried out for the three working conditions respectively.

The data obtained from 50 cycle tests are segmented according to the road segment length of 50 meters. As mentioned earlier, there are 1,700 sets of data for urban road sections, 2,400 sets for suburban 1 road sections, 2,450 sets for suburban 2 road sections, and 10,450 sets for expressway sections, with a total of 17,000 sets of data obtained. Among them, 84% are used as the training set, 6% as the validation set, and 6% as the test set. Therefore, 3 cycles are selected from the 50 cycles of each working condition to compare with the prediction results obtained by the BP neural network. The input layer includes 3 selected sequences of vehicle speed characteristic parameters, and the output layer is the cumulative energy consumption within the prediction window of the segment. Table 3 shows the parameters of the energy consumption prediction network.

Table 3. Parameters of the energy consumption prediction network

Model Parameter	Value
Input Layer	3 units
Hidden Layer 1	12 units
Hidden Layer 2	12 units
Output Layer	1 unit
Training Function	trainlm
Training Epochs	200
Step Size	10^{-5}
Maximum Failed Epochs	100
Minimum Performance Parameter	10^{-8}
Normalization Function	mapminmax

Among them, the transfer function of Hidden Layer 1 is logsig, and the transfer function of Hidden Layer 2 is purelin.

After the energy consumption prediction neural network is generated, the characteristic parameters of the 3 cycles in the test set are input into the neural network to generate the predicted energy consumption sequence, which is compared with the actual energy consumption sequence to evaluate the accuracy of the prediction model. The common evaluation indicators for the accuracy of prediction models include Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Square Error (MSE). The expressions of each indicator are as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i^o - \hat{y}_i^o|}{y_i^o} \times 100\% \tag{24}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i^o - \hat{y}_i^o| \tag{25}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^o - \hat{y}_i^o\right)^2} \tag{26}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i^o - \hat{y}_i^o\right)^2 \tag{27}$$

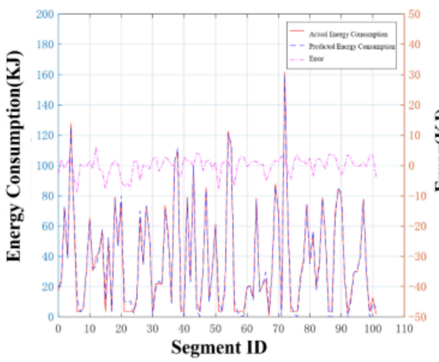
Where: y_i^o is the predicted value, $\hat{y}_i^o$ is the actual value, and n is the number of segments included in the entire road section.

Since the actual value may be 0 in the prediction, MAPE cannot be used because the denominator cannot be 0, and RMSE and MSE belong to the same type of indicators, so only MAE and RMSE are used in this paper.

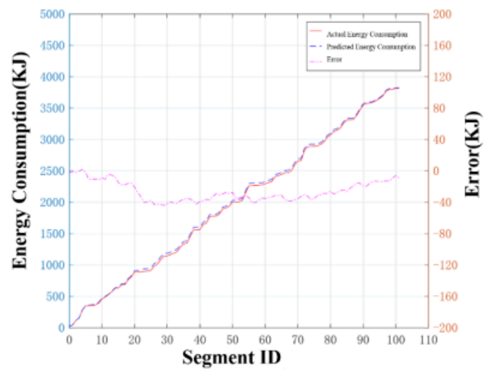
Table 4. Performance of energy consumption prediction

Road Condition	MAE/KJ	RMSE/KJ
Urban	0.0992	5.3301
Suburban 1	0.5690	8.6945
Suburban 2	0.2040	8.6270
Expressway	0.4221	4.0928

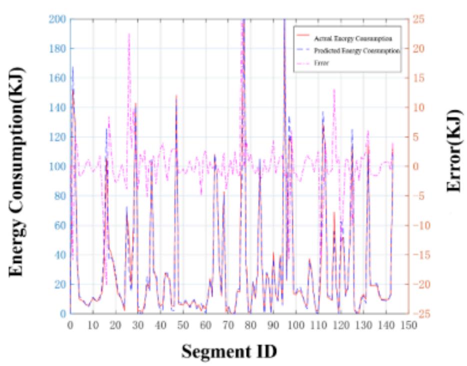
As shown in Table 4 and Figure 4, the BP neural network has a better energy consumption prediction effect under expressway and urban road conditions, and a slightly worse effect under suburban road conditions. In general, the BP neural network achieves relatively accurate energy consumption prediction under all road conditions, indicating that the driving energy consumption prediction based on vehicle speed characteristic parameters has high reliability and accuracy.



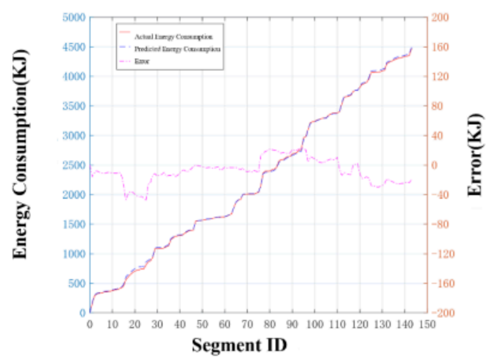
(a) Urban road segment



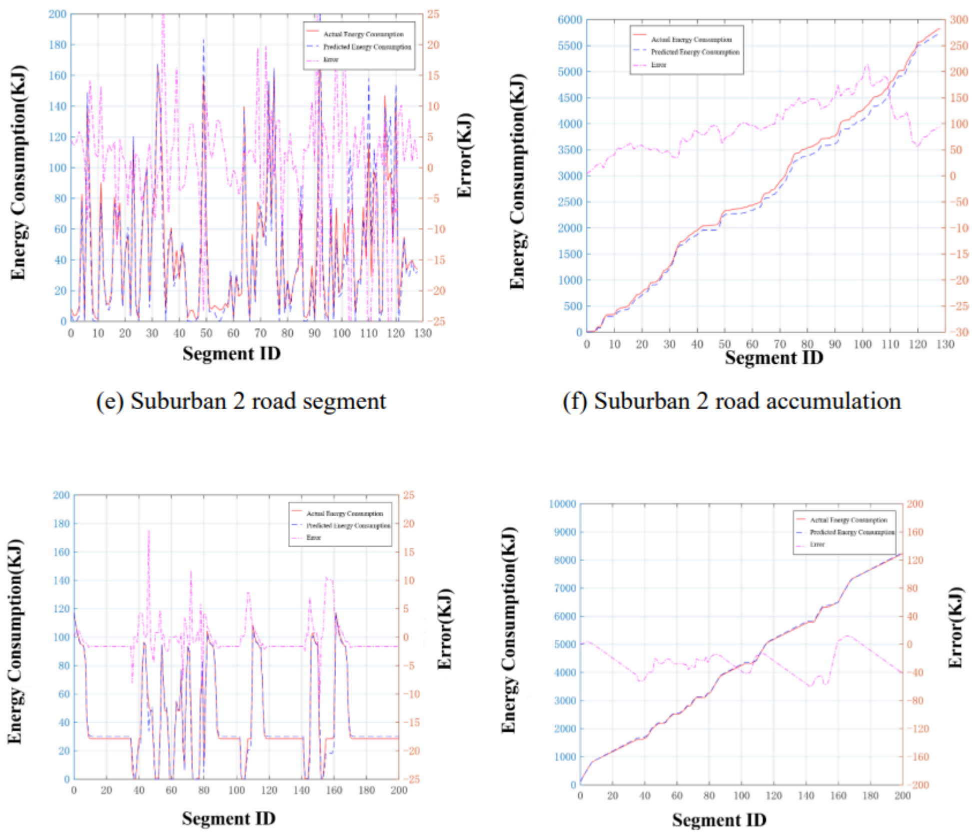
(b) Urban road accumulation



(c) Suburban 1 road segment



(d) Suburban 1 road accumulation



(e) Suburban 2 road segment

(f) Suburban 2 road accumulation

(g) Expressway road segment

(h) Expressway road accumulation

Figure 4. Energy consumption prediction based on actual vehicle speed characteristics

3.3. Vehicle speed characteristic parameter prediction neural network

The number of data groups collected for predicting vehicle speed characteristic parameters is the same as that in the previous section, with 84% used as the training set, 6% as the validation set, and 6% as the test set. Therefore, 3 cycles are selected from the 50 cycles of each working condition to compare with the prediction results obtained by the BP neural network.

The input layer includes the vehicle speed characteristic parameters of the previous segment of the predicted segment and 4 road traffic characteristic parameters (one-way driving distance dis, road type road, traffic congestion degree tra, and road speed limit spl); the output layer is 1 vehicle speed characteristic parameter.

Three different vehicle speed characteristic parameter prediction networks are generated for each working condition respectively. Table 5 shows the parameters of the vehicle speed characteristic prediction network.

Table 5. Parameters of the vehicle speed characteristic prediction network

Model Parameter	Value
Input Layer	5 units
Hidden Layer 1	12 units
Hidden Layer 2	12 units
Output Layer	1 unit
Training Function	trainlm
Training Epochs	200
Step Size	10^{5}
Maximum Failed Epochs	100
Minimum Performance Parameter	10^{-8}
Normalization Function	mapminmax

Among them, the transfer function of Hidden Layer 1 is logsig, and the transfer function of Hidden Layer 2 is purelin. Table 6 shows the prediction performance of vehicle speed characteristics under different road conditions.

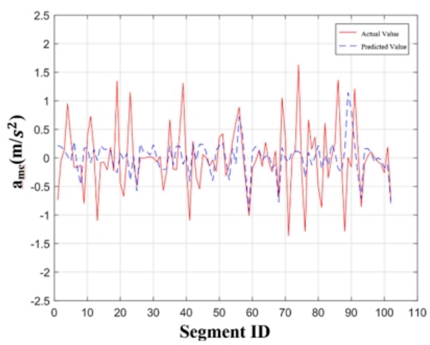
Table 6. Performance of vehicle speed characteristic prediction

Road Condition	Characteristic Parameter	MAE	RMSE
Urban	va_{max} (m^2/s^3)	1.3025	9.1603
	P_a (1)	0.0214	0.6502
	a_{me} (m/s^2)	0.06235	0.5860
Suburban 1	va_{max} (m^2/s^3)	0.0631	10.7858
	P_a (1)	0.0041	0.2510
	a_{me} (m/s^2)	0.0213	0.5946
Suburban 2	P_a (1)	0.0354	0.2202
	va_{max} (m^2/s^3)	0.1824	10.3506
	a_{me} (m/s^2)	0.0009	0.6117
Expressway Road Condition	a_{me} (m/s^2)	0.0062	0.5194
	va_{max} (m^2/s^3)	0.5415	8.3446
	a_{max} (m/s^2)	0.0106	0.3471

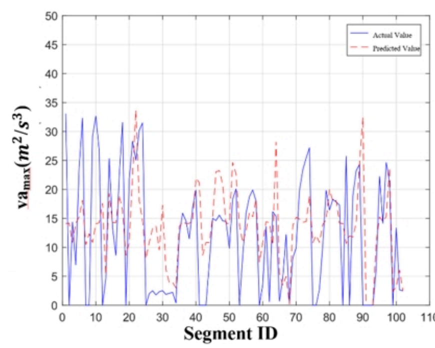
As shown in Figure 5, from a horizontal comparison, the prediction effect of acceleration proportion is not very ideal, especially for road sections where the acceleration proportion is 0 or 1, i.e., sections with no acceleration throughout and sections with acceleration throughout. The prediction of the BP neural network is "not bold enough" due to the result of synthesizing a large amount of data, and cannot accurately predict a small number of extreme data, which may be due to the clear boundaries on both sides of the input. On the other hand, the occurrence of this small number of extreme data is not highly correlated with the input. However, for most of the data, it can be considered that the prediction of the BP neural network is relatively consistent with the actual value.

From a vertical comparison, the prediction effect of vehicle speed characteristic parameters under urban road conditions is not very ideal, which may be due to the large number of parking and starting actions under urban congested road conditions. On the one hand, as an average value, the vehicle speed characteristic parameters may be greatly affected by the degree of traffic congestion. The prediction of vehicle speed characteristic parameters with a larger prediction window and more refined traffic congestion degree may obtain more stable and accurate characteristic parameters, but relatively, a longer prediction window will reduce the number of training sets of the energy consumption prediction neural network.

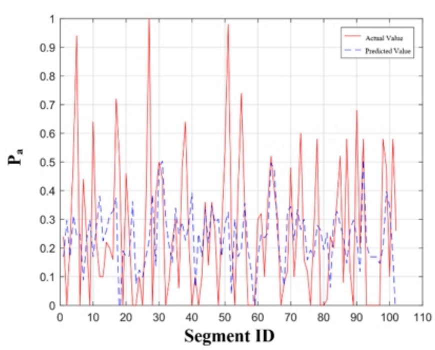
The difference between the predicted value and the actual value of the vehicle speed characteristic parameters oscillates around 0, so it can be considered that the error of the vehicle speed characteristic parameters has no superposition effect on the error of the final total energy consumption prediction.



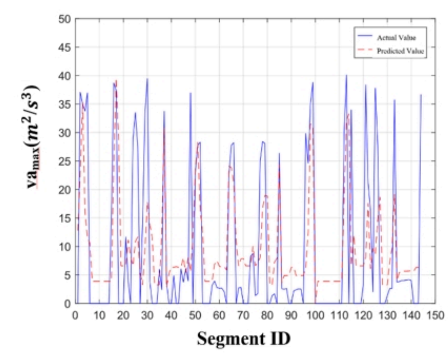
(a) a_{me} prediction under urban road condition



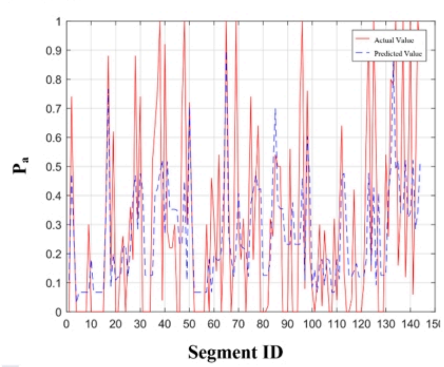
(b) va_{max} prediction under urban road condition



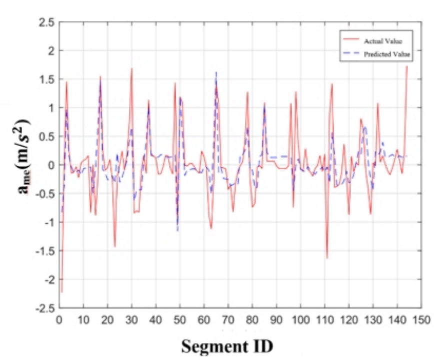
(c) P_a prediction under urban road condition



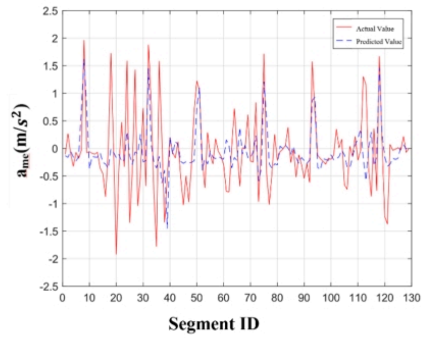
(d) va_{max} prediction under suburban 1 road condition



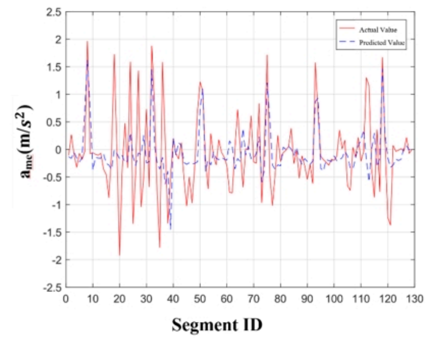
(e) P_a prediction under suburban 1 road condition



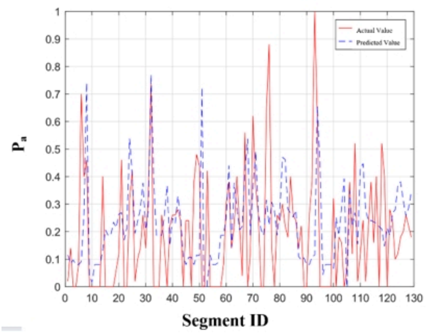
(f) a_{me} prediction under suburban 1 road condition



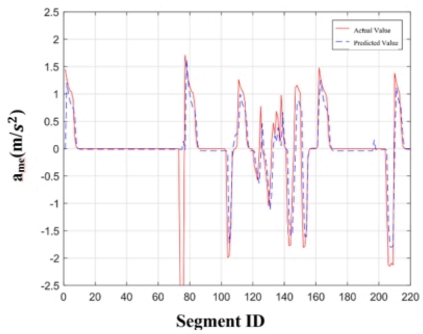
(g) a_{me} prediction under suburban 2 road condition



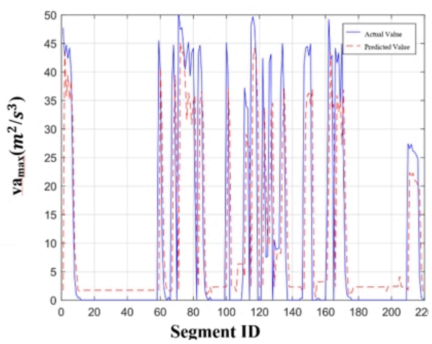
(h) va_{max} prediction under suburban 2 road condition



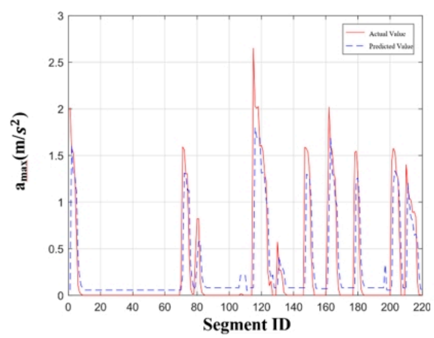
(i) P_{a} prediction under suburban 2 road condition



(j) a_{me} prediction under expressway road condition



(k) va_{max} prediction under expressway road condition



(l) a_{max} prediction under expressway road condition

Figure 5. Vehicle speed characteristic parameter prediction

3.4. Prediction of the two-level energy consumption prediction model

For each type of road condition, a sequence of road traffic characteristic parameters from one random cycle is extracted from the 50 cycles of data as the input of the two-level energy consumption prediction model. After inputting the corresponding sequence of road characteristic parameters, the three vehicle speed characteristic prediction neural networks under each road condition generate the corresponding sequence of vehicle speed characteristic parameters, which are then input into the energy consumption prediction model to output the corresponding sequence of segmented energy consumption.

Table 7. Energy consumption prediction performance based on predicted vehicle speed characteristics

Road Condition	MAE/KJ	RMSE/KJ
Urban	1.149	37.6719
Suburban 1	1.4734	14.1545
Suburban 2	0.9499	44.1652
Expressway	1.8116	44.5875

Table 7 shows the energy consumption prediction performance based on predicted speed characteristics. Since this paper aims at long-term energy consumption prediction, it is necessary to verify the prediction accuracy of the total driving energy consumption of various roads. The Relative Error (RE) shown in Formula (28) is introduced for error analysis. The relative error of driving energy consumption prediction under various road conditions is shown in Table 8.

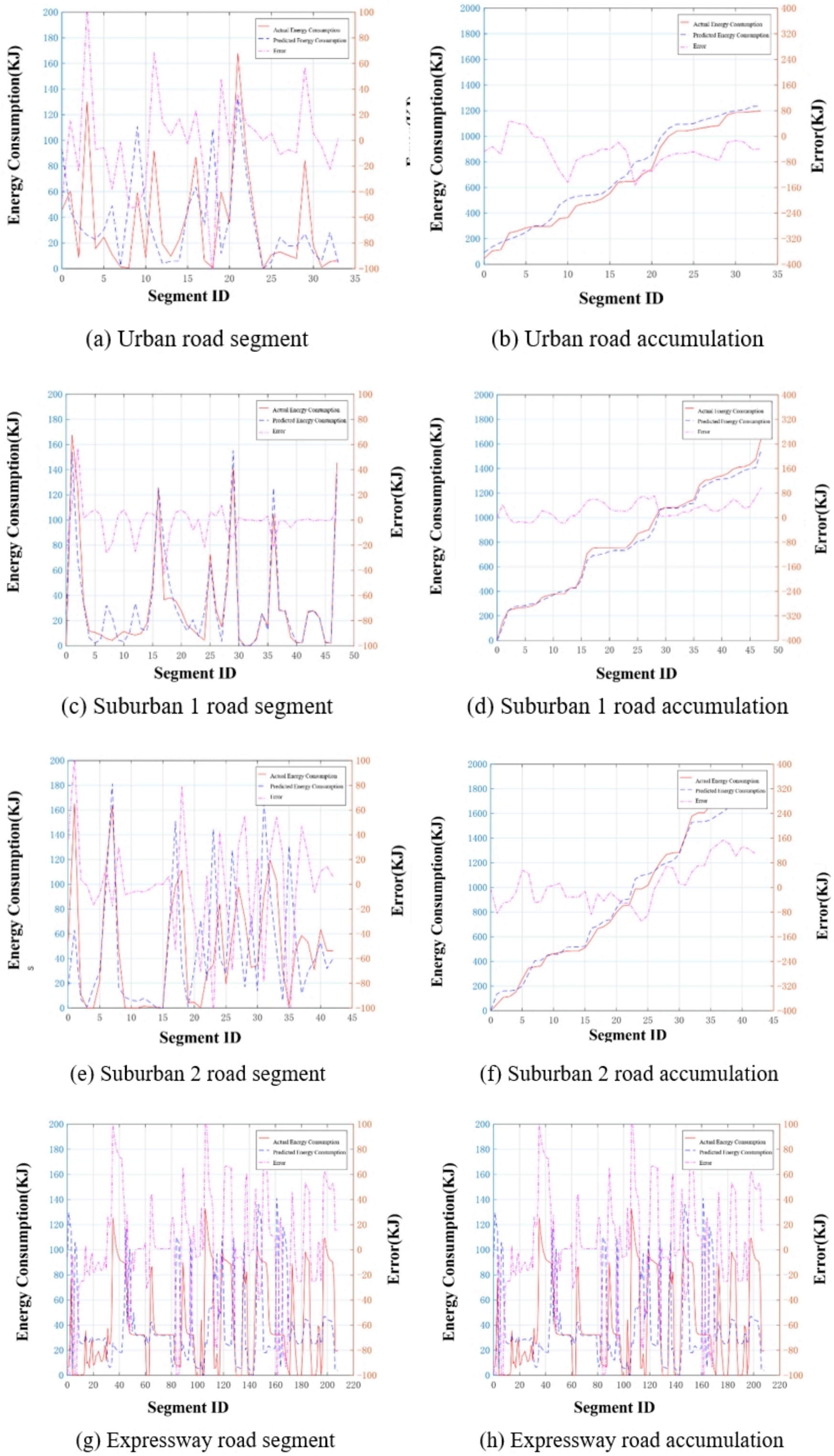
$$RE = \frac{\left|\widehat{E}_{total} - E_{total}\right|}{E_{total}} \tag{28}$$

Table 8. Total segment energy consumption prediction error

Road Condition	Relative Error	Prediction Accuracy
Urban	5.71%	94.29%
Suburban 1	4.37%	95.63%
Suburban 2	4.71%	95.29%
Expressway	3.84%	96.16%

As shown in Figure 6, compared with the energy consumption prediction obtained from the actual vehicle speed characteristic parameters, the MAE and RMSE of the energy consumption prediction obtained from the predicted vehicle speed characteristic parameters have a slight increase. Combined with the prediction results of vehicle speed characteristic parameters, it can be considered that the main error of this two-level energy consumption prediction model comes from the vehicle speed characteristic parameter prediction link. Nevertheless, the absolute error value of the driving energy consumption prediction of each segment changes up and down around 0, which makes the errors cancel each other out when calculating the total cumulative energy consumption, thus ensuring the prediction accuracy of the entire road even when the prediction error of some segments is large.

Long-time vehicle speed characteristic prediction performs better than long-time speed prediction to a certain extent. The essential reason is that a large part of driving energy consumption is acceleration energy consumption generated by acceleration, and the energy consumption prediction based on vehicle speed characteristics can fully consider the influence of dynamic characteristics such as acceleration and deceleration of vehicle driving on driving energy consumption.



(a) Urban road segment

(b) Urban road accumulation

(c) Suburban 1 road segment

(d) Suburban 1 road accumulation

(e) Suburban 2 road segment

(f) Suburban 2 road accumulation

(g) Expressway road segment

(h) Expressway road accumulation

Figure 6. Two-level energy consumption prediction based on vehicle speed characteristic parameters

3.5. Summary of this chapter

This chapter first introduces the relevant principles of the BP neural network, then uses the road traffic characteristic parameters, vehicle speed characteristic parameters and segmented energy consumption obtained in the previous chapter to train the BP neural networks for vehicle speed characteristic parameter prediction based on road traffic characteristic parameters under three road conditions. Then, a set of road traffic characteristic parameter sequences of four road sections are extracted from the dataset respectively, and the two-level energy consumption prediction model is used for energy consumption prediction, which is compared with the actual energy consumption for error analysis. Experiments show that the driving energy consumption prediction based on long-time vehicle speed characteristic parameters in this paper meets the expected prediction accuracy requirements.

4. Conclusion and prospect

4.1. Research conclusion

The main work of this paper is as follows:

(1) Using the research ideas and methods of energy consumption prediction based on vehicle speed characteristic parameters, the road traffic characteristic parameters, vehicle speed characteristics and energy consumption of the experimental road sections are calculated. Correlation analysis is carried out between energy consumption and vehicle speed characteristics to select appropriate vehicle speed characteristic parameters.

(2) A two-level energy consumption prediction model consisting of a vehicle speed characteristic parameter prediction model and a driving energy consumption prediction model based on vehicle speed characteristics is established. Finally, the verification and analysis of the model show that the driving energy consumption prediction method in this paper has a small error in the energy consumption prediction of the entire planned route.

Through the energy consumption prediction of the planned route, drivers can combine the remaining power of electric vehicles to make more reasonable travel plans.

4.2. Research prospect

This paper has the following shortcomings that can be further improved:

The sample data collected in this paper is limited. In the future, experiments can be carried out in different locations and more working conditions to verify whether the prediction models generated under the same working conditions in different locations have generalization ability, and whether the various levels of parameters under different working conditions have obvious differences.

As mentioned earlier, this paper only considers the driving energy consumption and does not take into account the energy consumption during parking due to the adoption of *v-dis* data instead of *v-t* data. The data collected through the APP includes the degree of road congestion. The curve of electric vehicle parking energy consumption with parking time can be obtained through experimental measurement, as well as the parking time sequence of the test vehicle under different road congestion degrees, so as to obtain the influence of road congestion degree on parking energy. During prediction, the parking energy is predicted according to the congestion degree of each segment on the planned route, and this part of energy is added to the energy consumption prediction in this paper.

Different from traditional vehicles, electric vehicles have the characteristic of energy recovery during deceleration and parking. During deceleration, electricity is generated through motor braking, and the electric energy can be recovered into the battery pack, which will reduce the overall energy consumption. This part of energy is not considered in this paper for the sake of simplified calculation.

On the basis of the driving energy consumption prediction method based on vehicle speed characteristics adopted in this paper, an energy management strategy can be designed and optimized according to the real-time information on the planned driving route, and the energy system can be globally planned and optimized managed, so that electric vehicles can make full use of electric energy and improve economic efficiency along the entire planned route.

References

[1] Brandstetter, P., Vanek, J., & Verner, T. (2014). Electric vehicle energy consumption monitoring. In *Proceedings of the 2014 15th International Scientific Conference on Electric Power Engineering (EPE)* (pp. 589-592). IEEE.
[2] De Cauwer, C., Van Mierlo, J., & Coosemans, T. (2015). Energy consumption prediction for electric vehicles based on real-world data. *Energies, 8*(8), 8573-8593.
[3] Morlock, F., Rolle, B., Bauer, M., & Sawodny, O. (2019). Forecasts of electric vehicle energy consumption based on characteristic speed profiles and real-time traffic data. *IEEE Transactions on Vehicular Technology, 69*(2), 1404-1418.
[4] Uemura, T. (2019). Pre-estimation of electric vehicle energy consumption on unfamiliar roads and actual driving experiments. In I. Bartolini & F. Li (Eds.), *Proceedings of the VLDB 2019 PhD Workshop, co-located with the 45th International Conference on Very Large Databases (VLDB 2019)*, Los Angeles, California, USA, August 26-30, 2019 (Vol. 2399). CEUR-WS.org.
[5] Wu, X., Freese, D., Cabrera, A., & Kitch, W. A. (2015). Electric vehicles' energy consumption measurement and estimation. *Transportation Research Part D: Transport and Environment, 34*, 52-67.
[6] Krogh, B., Andersen, O., & Torp, K. (2015). Analyzing electric vehicle energy consumption using very large data sets. In *International Conference on Database Systems for Advanced Applications* (pp. 471-487). Cham: Springer International Publishing.
[7] Al-Wreikat, Y., Serrano, C., & Sodré, J. R. (2022). Effects of ambient temperature and trip characteristics on the energy consumption of an electric vehicle. *Energy, 238*, 122028.
[8] Zhu, Q., Huang, Y., Lee, C. F., Liu, P., Zhang, J., & Wik, T. (2024). Predicting electric vehicle energy consumption from field data using machine learning. *IEEE Transactions on Transportation Electrification, 11*(1), 2120-2132.
[9] Feng, Z., Zhang, J., Jiang, H., Yao, X., Qian, Y., & Zhang, H. (2024). Energy consumption prediction strategy for electric vehicle based on LSTM-transformer framework. *Energy, 302*, 131780.
[10] Wang, Y., Huang, H., Hao, R., Luo, L., & He, H. D. (2025). Prediction of Battery Electric Vehicle Energy Consumption via Pre-Trained Model Under Inconsistent Feature Spaces. *Technologies, 13*(11), 493.
[11] Hussain, I., Ching, K. B., Uttraphan, C., Tay, K. G., Noor, A., & Memon, S. A. (2025). Optimizing electric vehicle energy consumption prediction through machine learning and ensemble approaches. *Scientific Reports, 15*(1), 29065.
[12] Khan, A., Iqbal, N., Kaleem, Z., Qarnain, Z., & Bait-Suwailam, M. M. (2025). A multi-model approach for predicting electric vehicle specifications and energy consumption using machine learning. *The Journal of Supercomputing, 81*(1), 314.
[13] Bagheri, E., Tehrani, M. M., Azadi, M., & Moosavian, A. (2025). Impact of driving characteristic parameters and vehicle type on fuel consumption and emissions performance over real driving cycles. *PLoS One, 20*(1), e0317098.
[14] De Winter, J. C., Gosling, S. D., & Potter, J. (2016). Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: A tutorial using simulations and empirical data. *Psychological methods, 21*(3), 273.

[15] Montazeri-Gh, M., Fotouhi, A., & Naderpour, A. (2011). Driving patterns clustering based on driving features analysis. Proceedings of the Institution of Mechanical Engineers, Part C: *Journal of Mechanical Engineering Science, 225*(6), 1301-1317.

[16] Li, M. (2024). Comprehensive review of backpropagation neural networks. *Academic Journal of Science and Technology, 9*(1), 150-154.

[17] Alkhasawneh, M. S. (2021). A comparison between seven heuristic methods to estimate the number of hidden layer neurons in a multi layer perceptron neural network. *International Journal of Advanced Trends in Computer Science and Engineering, 10*(2), 955–963.

[18] Basheer, I. A., & Hajmeer, M. (2000). Artificial neural networks: fundamentals, computing, design, and application. *Journal of microbiological methods, 43*(1), 3-31.

[19] Widrow, B., & Lehr, M. A. (2002). 30 years of adaptive neural networks: perceptron, madaline, and backpropagation. *Proceedings of the IEEE, 78*(9), 1415-1442