American Journal of Electrical and Computer Engineering
2022; 6(2): 91-98
http://www.sciencepublishinggroup.com/j/ajece
doi: 10.11648/j.ajece.20220602.15
ISSN: 2640-0480 (Print); ISSN: 2640-0502 (Online)

Research on Working Characteristics Prediction of Passenger Vehicle Shock Absorber Based on Deep Learning

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To cite this article:

Jinyun Chang, Xuewu Zhu, Chao Han, Xingming Zhao, Jiaxing Sun. Research on Working Characteristics Prediction of Passenger Vehicle Shock Absorber Based on Deep Learning. *American Journal of Electrical and Computer Engineering*. Vol. 6, No. 2, 2022, pp. 91-98. doi: 10.11648/j.ajece.20220602.15

Received: November 25, 2022; **Accepted**: December 16, 2022; **Published**: December 29, 2022

Abstract: The shock absorber is an important component of the automobile suspension system, which mainly plays the role of attenuating vibration during the driving of the car. The shock absorber is subjected to complex alternating loads during the recovery and compression process, and its dynamic damping characteristics show strong nonlinearity. The dynamic performance of the shock absorber has an important impact on the vehicle ride comfort and handling stability, so it is of great significance to carry out the prediction research on the working characteristics of the shock absorber. This paper introduces the structure and working principle of an automobile hydraulic shock absorber, and analyzes the reasons for the high nonlinearity of the working characteristics of the shock absorber. A prediction method and implementation framework of shock absorber working characteristics based on long short memory neural network (LSTM) algorithm are proposed, and abundant sample data are obtained through passenger vehicle durability test and shock absorber bench test. The effectiveness of feature selection is verified by data preprocessing and distribution law statistics. Finally, the LSTM intelligent algorithm is used to train, verify and test the sample data, and a prediction model of the working characteristics of the shock absorber is established. By comparing with the actual working characteristics data of the shock absorber, the accuracy and applicability of the prediction model are verified.

Keywords: Working Characteristics of Shock Absorber, Deep Learning Algorithm, LSTM, Dynamic Response Prediction

1. Introduction

The suspension system is an important chassis component that affects the ride comfort and handling stability of passenger vehicles, and is able to transmit dynamic loads from the road surface [1, 2]. On a smooth road surface, the spring in the suspension can transmit most of the road excitation. As the road environment becomes more complex, the spring absorbs the impact of the road surface, but will cause violent shaking of the body due to its own recovery deformation. The shock absorber can reduce the impact of vibration and improve driving comfort due to its special dynamic damping characteristics [3]. The accurate prediction of the working characteristics of the shock absorber has become an important index to evaluate its vibration isolation performance.

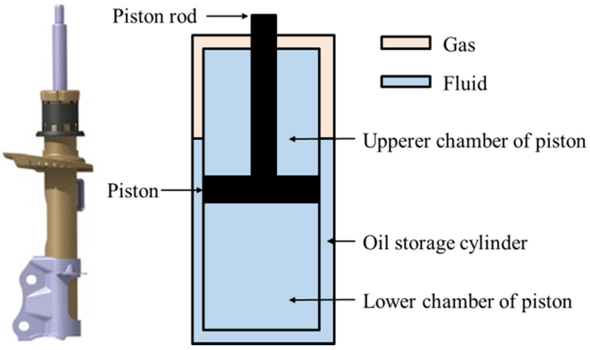


Figure 1. *Structure of shock absorber.*

At present, the most widely studied shock absorber is hydraulic shock absorber [4], as shown in Figure 1. During recovery and compression process, the oil flows in the shock absorber, forming a pressure difference between the cavities, generating a damping force to inhibit the motion of the shock absorber, thereby achieving the purpose of attenuating vibration. However, the valve system structure within the shock absorber is relatively complex and cannot rely on simple linear functions to characterize the working characteristics.

Many scholars study the dynamic characteristics of the shock absorber by establishing physical parameter model, equivalent parametric model and non-parametric model [5]. Lang established a shock absorber model with 83 parameters, which can simulate and calculate the dynamic characteristics of the shock absorber [6]. Huang Sheng established the mathematical model of the shock absorber by using ADAMS software, and obtained the characteristic curve of the shock absorber through simulation [7]. Liu Dezhu established AMESim model of shock absorber to predict dynamic damping characteristics, and obtained high accuracy by modifying parameters [8]. Compared with the above methods, the physical parameter model is difficult to popularize and apply due to the large number of parameters and the extremely complex establishment process. The equivalent parametric model and non-parametric model have fast modeling speed, but it is difficult to fully consider the complex nonlinear characteristics of the shock absorber, and the modeling process depends on the structural parameters of the actual shock absorber.

With the development of computer simulation technology and intelligent recognition algorithms, the demand for wire control of automobile suspension system is gradually increasing. In order to improve the controllability of shock absorber performance, a prediction model for the working characteristics of shock absorbers based on deep learning is proposed, which can fully consider the highly nonlinear damping characteristics of the shock absorber. This method takes intelligent algorithm as the core and real-time data of the passenger vehicle as the drive to quickly and accurately predict the dynamic response of the shock absorber. By accurately predicting the test data, the superiority of this method for predicting the complex working characteristics of shock absorbers is verified.

2. Principles of Deep Learning

Deep learning has high nonlinear parameter fitting ability, and can approximate arbitrary continuous functions when containing enough neuron units and hidden layers [9]. For the time series data generated during vehicle driving, the data before and after the series has a strong correlation, and the prediction effect of traditional neural network is not ideal. For this type of problem, the recurrent neural network can solve the difficulty of time correlation well, remember the correlation information, and effectively mine the characteristics of time series.

2.1. Recurrent Neural Network

Recurrent Neural Network (RNN) is a class of network models with short-term memory capabilities [10]. The network structure contains input layer, hidden layer and output layer. The hidden layer neurons can not only accept the information of other neurons, but also accept their own information at historical moments. Compared with the traditional neural network, RNN has an additional loop in the hidden layer neurons. The output h_t at the current moment is affected by the combination of the input of the current moment and historical data (Figure 2).

Theoretically, RNN can deal with the long-term dependence of arbitrary time series data and extract the long-term features implied in the data [11-12]. Due to the problems of gradient dissipation and gradient explosion, RNN can only deal with short-term dependent sequences. The sampling rate of vehicle dynamic load data is high, and the short-term time series cannot reflect the long-term dependence between dynamic loads.

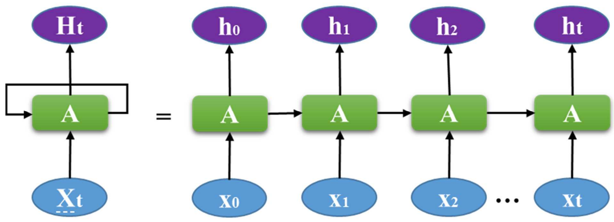


Figure 2. *Neuron structure of RNN hidden layer.*

2.2. Long Short-Term Memory Neural Network

Long Short-term Memory Neural Network (LSTM), which is essentially a recurrent neural network, has more obvious advantages than RNN in solving long-sequence time data problems [13-15]. The difference between LSTM and RNN lies in the structure of hidden layer neurons (Figure 3). LSTM adds input gate, output gate and forgetting gate inside neurons to transmit and mine data features, flexibly adjust the weights of important features, and retain more valuable information [16].

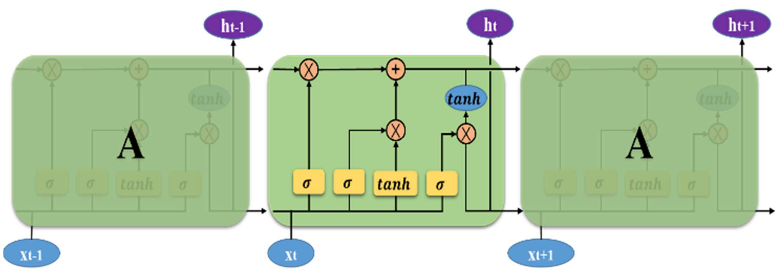


Figure 3. *Neuron structure of LSTM hidden layer.*

The forgetting gate decides which unimportant information is discarded in the neuron, and selectively retains the important information in the time series through the sigmoid activation function. The forgetting gate is calculated as follows, σ represents the activation function, h_{t-1} represents the output at the previous moment, x_t represents the input at the current moment, W_f represents the weight, and b_f represents the threshold.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

The input gate determines how much new information is retained in the neuron, the sigmoid layer determines which information will be updated, and the tanh layer retains alternative information that can be updated. The calculation of the input gate is as follows:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{3}$$

The output gate outputs useful information through Sigmaid and tanh activation functions. The calculation formula is as follows:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{4}$$

$$h_t = o_t * \tanh(C_t) \tag{5}$$

3. LSTM Driven Shock Absorber Working Characteristics Prediction Method

The working state of the shock absorber changes continuously with the road environment, and the deep learning response prediction can establish the time series response relationship of key components with less road load data. It can directly fit the implicit relationship between related parameters. The working characteristics of the shock absorber are reflected in the change of the force with the displacement under different motion attitudes. This method takes the test load data as the input and the shock absorber dynamic response as the output, and predicts the working characteristics of the shock absorber through the multi-layer network structure. The specific scheme is shown in Figure 5. In this paper, key feature parameters are selected from the actual road load spectrum data of passenger vehicles, and high-quality initial data is obtained through multiple data processing methods such as outlier correction, filtering, and resampling, which is helpful to quickly and accurately mine data features. Then the LSTM algorithm is used to build the prediction model of the dynamic response of the shock absorber, and the high-precision prediction network is obtained through multiple network training and verification.

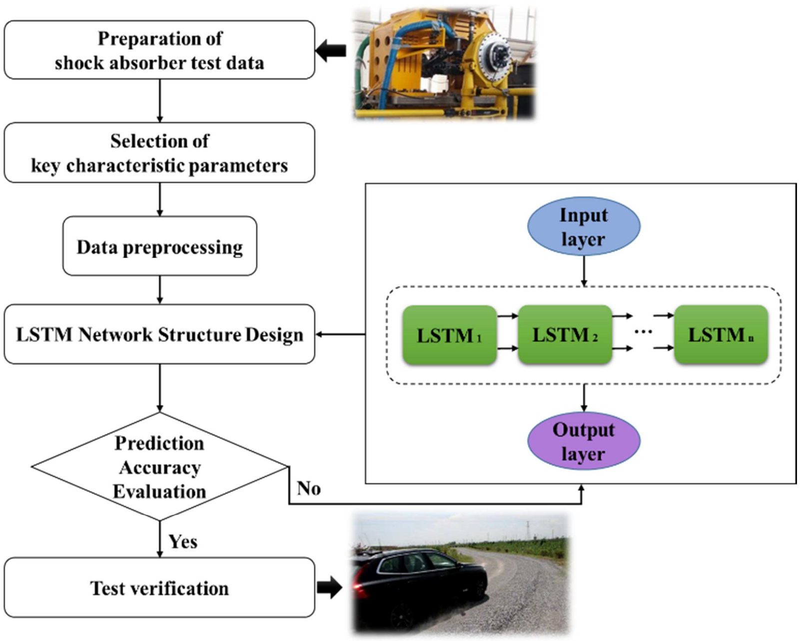


Figure 4. *Deep learning driven shock absorber working characteristics prediction framework.*

4. Test Data Preparation

Prediction of the working characteristics of the shock absorber depends on well-conditioned tests. First, the shock absorber bench test should be carried out to collect the force and displacement responses of the shock absorber under different loading frequencies. Then the relevant dynamic loads are collected by the vehicle durability load spectrum test as data storage.

4.1. Shock Absorber Bench Test Data Collection

The bench test is the main way to study the dynamic characteristics of the shock absorber, which can check whether the performance of the shock absorber is qualified, and can also provide a practical reference for the simulation analysis of the whole vehicle. In this paper, the force and displacement data of the shock absorber are collected through a test bench. The working principle and test method are shown in Figure 5.

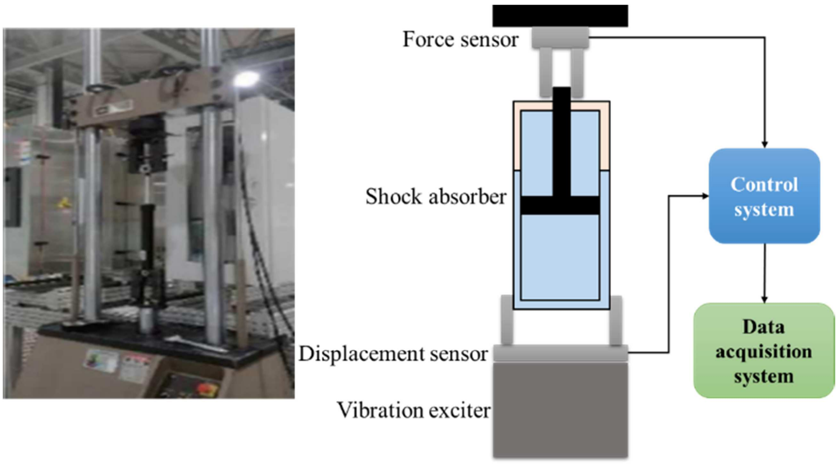


Figure 5. *Data collection of shock absorber bench test.*

4.2. Passenger Vehicle Durability Test Data Collection

During the durability load spectrum test of passenger vehicles, the data collection work fully considers the load demand of key parts in the vehicle development, and can obtain the key load spectrum related to the health status of the whole vehicle life, such as body acceleration, suspension system travel, six-component force of wheel center, force and strain of parts, etc. The following shows the main acquisition parameters and test methods.

Table 1. *Data collection of passenger vehicle road load spectrum.*

Signal type	Collection object	Sensor
Force	Wheel center force Wheel center torque	
Displacement	Shock absorber displacement Suspension displacement	
Acceleration	Shaft head acceleration Body acceleration	
Strain	Strain of key parts	

5. Experimental Analysis

5.1. Parameter Selection and Preprocessing

During the test, relatively complete test data of the shock absorber were collected through sensors. The vehicle is a symmetrical model, considering that the working characteristics of the shock absorber are affected by the excitation of the road surface, this paper selects the six-component force of the left front wheel center as input features (Figure 6). The vertical force can reflect the influence of road unevenness, and the longitudinal and lateral force can reflects the effects of road obstacles and wheel steering. The original data sampling frequency is 500Hz, and the data in the frequency range of 0.6~60Hz is retained by filtering.

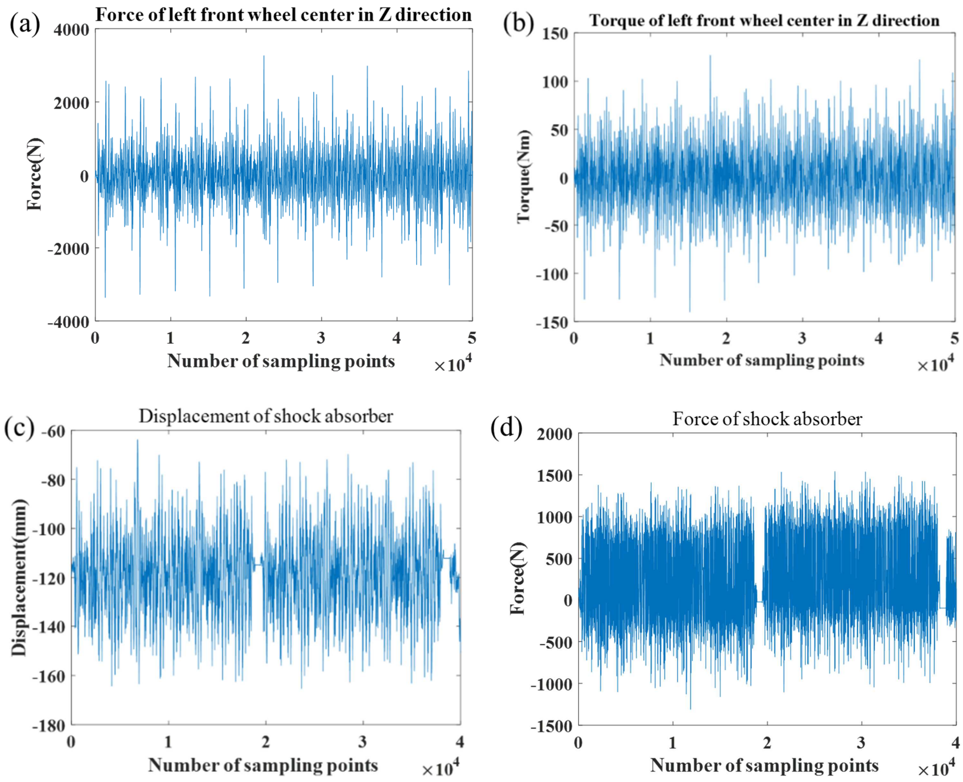
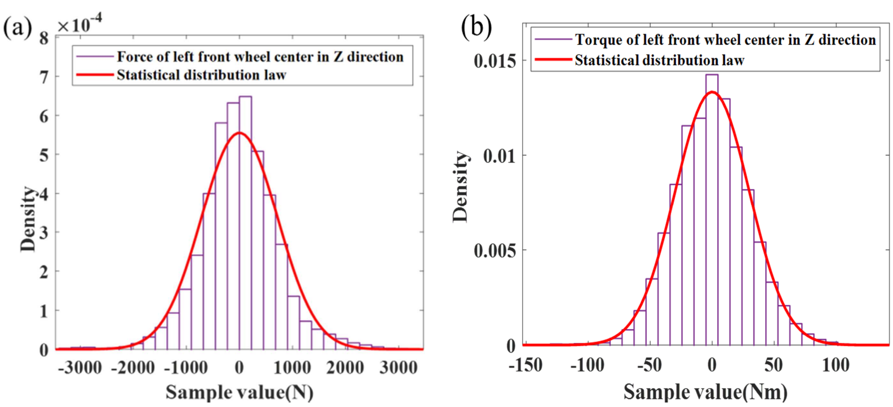


Figure 6. *Shock absorber test sample data.*

The sampling frequency of passenger vehicle road load spectrum data is high, and the distribution range of different characteristic parameters varies greatly. In order to make the algorithm quickly and accurately find the optimal solution, it is necessary to study the distribution law of the data, and then select an appropriate standardization method according to the distribution law.

It can be seen from the statistical distribution that the time-domain data of the six-component force of the left front wheel center and the dynamic response of the shock absorber basically satisfy the Gaussian distribution (Figure 7), which can be standardized by the Z-score method. The calculation formula is as follows, σ and μ represent the variance and mean of the initial data respectively.

$$Z = \frac{X-\mu}{\sigma} \tag{6}$$



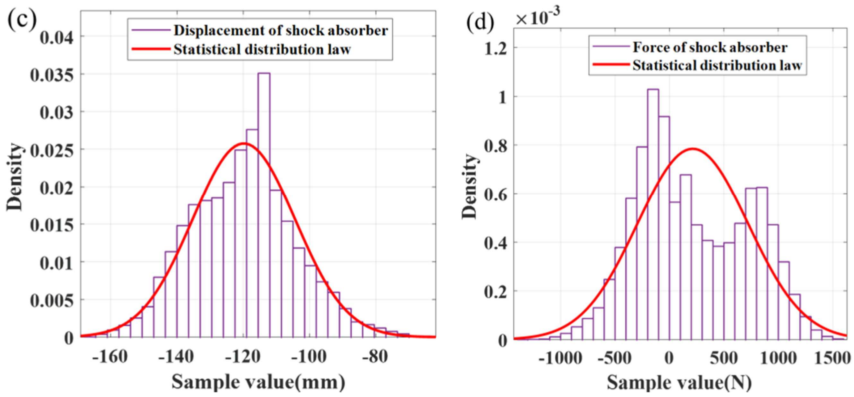


Figure 7. *Statistics of distribution law of test sample data.*

5.2. LSTM Network Structure Design

In this paper, the network structure is constructed by MATLAB software. First, the standardized six-component force of the left front wheel center of the passenger vehicle is used as the input of the LSTM neural network, and the shock absorber displacement is predicted by constructing a multilayer LSTM network. By adjusting the number of hidden layer neurons, the force prediction network structure of the shock absorber with the best performance is finally determined (Table 2).

Table 2. *Parameter settings of LSTM neural network for shock absorber displacement prediction.*

Parameter name	Parameter size
Training set	70%
Test set	30%
Iteration round	300
Initial learning rate	0.01
Number of input layer units	6
Number of LSTM layer units	64*64*32
Number of fully connected layer units	32
Number of output layer units	1

After accurately predicting the shock absorber displacement characteristics, the standardized displacement data of the shock absorber bench is used as the input to predict the force characteristics. The optimal network structure is shown in Table 3.

Table 3. *Parameter settings of LSTM neural network for shock absorber force prediction.*

Parameter name	Parameter size
Training set	70%
Test set	30%
Iteration round	300
Initial learning rate	0.01
Number of input layer units	1
Number of LSTM layer units	128*128*64*64
Number of fully connected layer units	32
Number of output layer units	1

5.3. Prediction Accuracy Evaluation and Test Verification

In order to verify the prediction effect of the prediction model, this paper selects the root mean square error (RMSE), mean absolute error (MAE) and other indicators commonly used in regression prediction problems to evaluate the prediction ability of the network, and selects the correlation coefficient (R^2) to evaluate the fitting relationship between real data and predicted data, where $\overline{y_{tset}}$ and $\overline{y_{predict}}$ represent the mean of the real data and predicted data respectively.

$$RMSE = \sqrt{\frac{\sum(y_{tset}-y_{predict})^2}{N}} \tag{7}$$

$$MAE = \frac{\sum|y_{tset}-y_{predict}|}{N} \tag{8}$$

$$R^2 = \frac{\sum(y_{tset}-\overline{y_{tset}})(y_{predict}-\overline{y_{predict}})}{\sqrt{\sum(y_{tset}-\overline{y_{tset}})^2} * \sqrt{\sum(y_{predict}-y_{predict})^2}} \tag{9}$$

5.3.1. Shock Absorber Displacement Prediction Effect

After several iterative calculations, a prediction model of the working characteristics of the shock absorber satisfying the prediction error is obtained. Real-time test data of the six-component force of the left front wheel center with a duration of 10s were randomly selected to predict the displacement of the shock absorber. The displacement of the shock absorber predicted by the LSTM algorithm is shown in Figure 8. There is a small error between the predicted value and the test value, and the prediction accuracy is high at the peak and trough of the curve, which proves that the model can accurately predict the displacement characteristics of the shock absorber.

In addition to the passenger vehicle durability test, the force and displacement calculation of the shock absorber is usually obtained through the dynamic simulation calculation of the ADAMS Car vehicle. It can be seen from Figure 9 that the LSTM prediction method has higher accuracy than the vehicle dynamics simulation method. RMSE and MAE are greatly reduced, and the accuracy is improved by 40.96% and 38.46% respectively. At the same time, R^2 has also increased by 7.78%, which proves that the prediction ability of the model has been enhanced. This is because the LSTM prediction algorithm can consider the nonlinear characteristics of the real environment, but there are some assumptions in the vehicle dynamics simulation, ignoring the influence of nonlinearity.

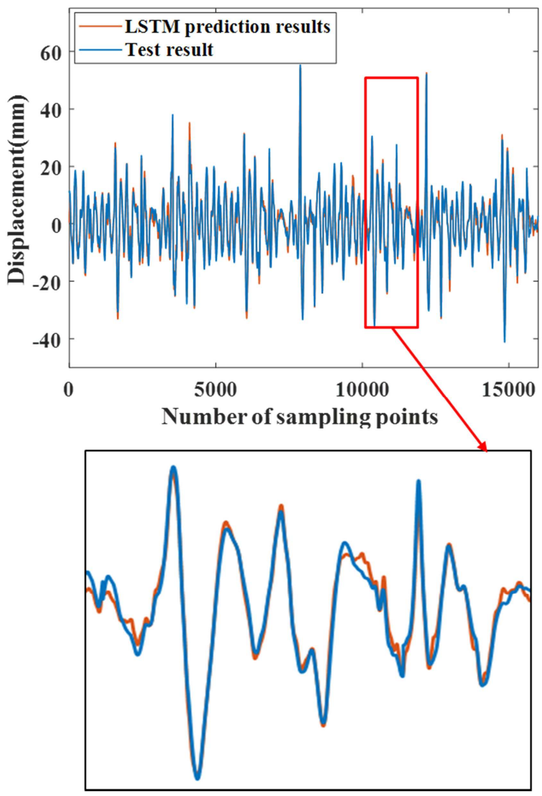


Figure 8. Prediction results of shock absorber displacement characteristics.

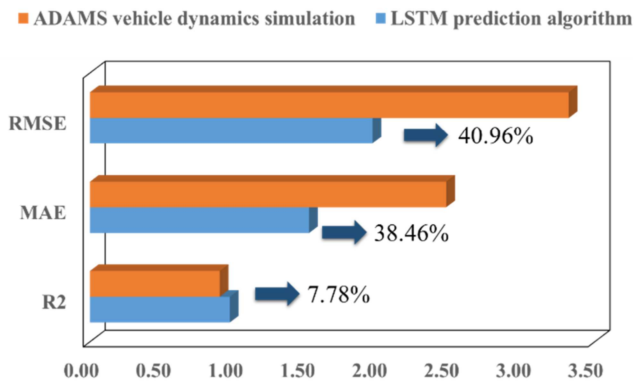


Figure 9. Accuracy comparison between LSTM algorithm and ADAMS vehicle dynamics simulation.

5.3.2. Shock Absorber Force Prediction Effect

After accurately predicting the displacement characteristics of the shock absorber, displacement data collected by the bench test is used as the model input to predict the real-time force state of the shock absorber. In order to show the high applicability of the prediction model, the forces around the 30s, 30min, 40min, and 50min moments in the time history data of the shock absorber are predicted. It can be seen from Figure 10 that there is a small error between the predicted value and the test value.

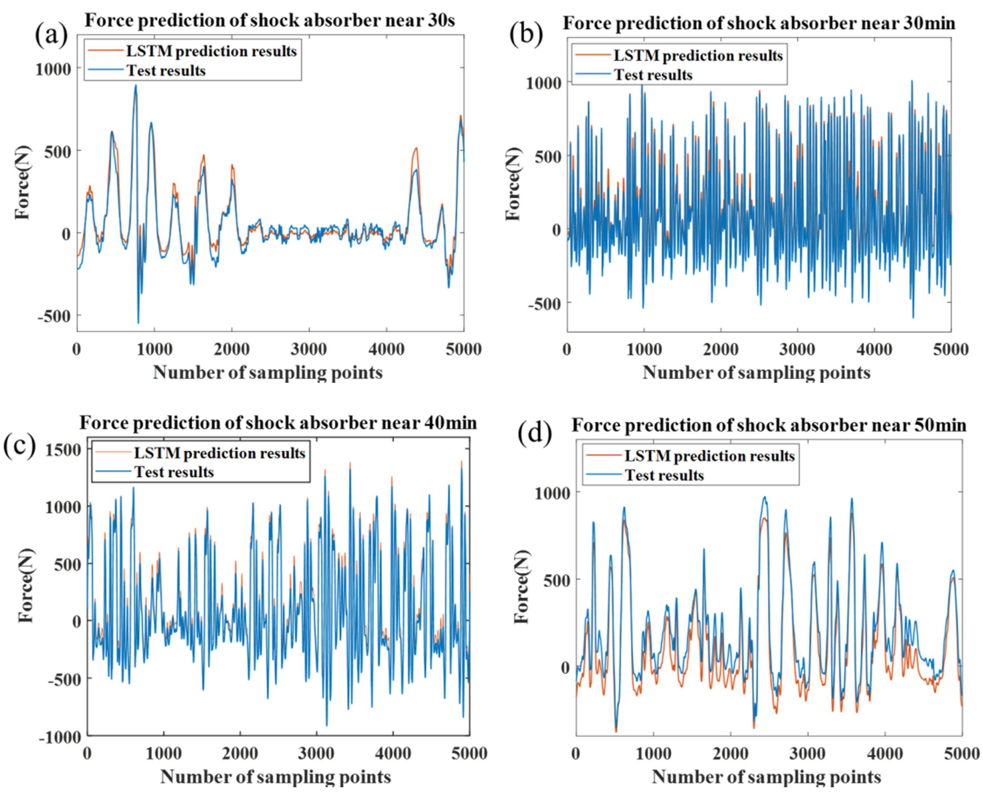


Figure 10. Prediction results of shock absorber force characteristics.

It can be seen from Table 4 that LSTM algorithm model has excellent performance ability in the whole test cycle of shock absorber working characteristics, and the force range of the shock absorber used in the test is about -1800~1800N, the maximum RMSE error in the test time is 126.86N, and the prediction error can be controlled within 7%.

Table 4. *Evaluation on the Prediction Accuracy of Shock Absorber Force in Bench Test.*

Forecast Period	RMSE (N)	MAE (N)	R^2
Near 30s	62.74	47.03	0.98
Near 30min	126.86	100.39	0.89
Near 40min	109.80	80.45	0.91
Near 50min	84.50	71.43	0.97

6. Conclusion

In this paper, a prediction method for the working characteristics of the shock absorber is proposed. Based on LSTM algorithm, a prediction model of the working characteristics of the shock absorber is established, and the model is driven by real-time vehicle durability test data and bench test data to update the predicted displacement characteristics and force characteristics of the shock absorber. The prediction results show that the LSTM algorithm can well identify the highly nonlinear characteristics of passenger vehicle shock absorbers, and has good prediction ability for long-period time series data.

In the process of durability development of passenger vehicle shock absorbers, this method can provide accurate load input for fatigue prediction of the whole life cycle of the shock absorber. Combined with the fatigue prediction algorithm, the fatigue life of the shock absorber can be calculated in real time, which is helpful to shorten the development cycle. At the same time, this method can provide attribute input of shock absorber for vehicle dynamics modeling, so as to improve the accuracy of vehicle dynamics simulation.

Acknowledgements

This research work was supported by FAW Hongqi C095 project. The authors thank the chassis test team of FAW Research and Development Institute for providing valuable test data.

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