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Identifying Dynamic Load of Air Suspension Based on Elman Neural Network

Bin Yang[1, 2, 3, a], Yongjun Li[2,3,b] and Ningwu Wang[2,3,c]

[1]*School of Automotive and Transportation, Tianjin University of Technology and Education Tianjin, China*
[2]*R & D Center of Great Wall Motor Company Limited, Baoding 071000, China*
[3]*Hebei Province Automotive Engineering Technology Research Center, Baoding 071000, China*
a.yangbinwindows@163.com b.lyj321163@163.com
c. xuewanmei_11@163.com

Abstract

Elman neural network was utilized to accomplish mapping from vibrant acceleration space of unsprung mass to dynamic load space in order to identifying results of neural network can more approach dynamic changing course of air suspension during active controlling process of air suspension. The dynamic model of 1/4 engineering vehicle was established. Vibrant acceleration data and dynamic load data were got by simulation based on the dynamic model of 1/4 engineering vehicle. Vibrant acceleration data were selected to be input data and dynamic load data were selected to be output of Elman neural network. Elman neural network was trained by input and output data. Then, generalization of trained Elman neural network was tested as follows. Sine wave was selected as road input. When amplitude was selected as 0.1m and frequency was selected as 1 rad/s, data of identifying error rate within 30％ took 75.97％ in total data. When amplitude was selected as 0.05m and frequency was selected as 0.5 rad/s, data of identifying error rate within 30％ took 96.1％ in total data. Results indicated that Elman neural network possess better fitting ability on this situation. When amplitude was selected as 0.3m and frequency was selected as 2 rad/s, results indicated that identifying error rate decreased and identifying curve obviously separated with numerical curve. It is perhaps for the reason that more identifying data scale out the value boundary of trained data. Meanwhile identifying curve and numerical curve gradually approached and stabilized eventually. It demonstrated that Elman neural network can effectively approach dynamic changing course of air suspension.

Keywords*: air spring; nonlinear; dynamic; Elman neural network*

1. Introduction

Because air spring is a sort of elastic parts and possesses characteristic of nonlinear and changing stiffness. So it can effectively improve ride comfort and handling stability of the automobile [1-2]. For higher and higher demand for ride comfort of the automobile, intelligent control of air suspension is a main way among total developing direction in order to make further improvement on the ride comfort and handling stability of the automobile [3].

The correlate parameter of the automobile must be identified if we want to achieve intelligent control to the automobile. Then the controlling signal can be calculated acting on the fixed controlling rules by the controller according to identifying results of the automobile. Reference [4] identified dynamic load of the air suspension system based on BP neural network. But BP neural network is a sort of static network, it can only establish mapping from the input data to the output data and it can't effectively approach dynamic changing course of the air suspension. So it exists a certain defect in the actual situation. This paper selected vibrant acceleration of unsprung mass as the input of Elman neural network, dynamic load of the air suspension as the output of Elman neural network. So dynamic could be identified according to vibrant acceleration of unsprung mass of the air suspension.

2. Working Principle of Air Spring

Air suspension consists of air spring, thrust bar, height control valve, shock absorber and stabilizer bar. Air spring is elastic part of the air suspension. Compressing air was selected as elastic media of the air spring. It accomplish its job by compression characteristic of the air. Air spring is a key part of air suspension.

During practical working course of air spring, air pressure value of the air spring must keep balance with outer load acted on air spring. Then

$$F=P\times A \tag{1}$$

F——outer load, N ; P——air pressure of air spring, Pa ; A——effective area of air spring, m^2.

Assuming equilibrium site of air spring to be origin, then its vertical displacement can be expressed as h in arbitrary instant and air pressure and effective area of air spring are all expressed as function of h. During practical working course of air spring, state of air alters rapidly and frequently and compressing air has not enough time to exchange amount of heat with outer space. So working course of air spring can be regarded as adiabat processing[7]. Then,

$$(P_0+P_a)V_0^m=(P+P_a)V^m \tag{2}$$

P_0——air pressure of air spring at equilibrum site, Pa ; Pa——atmosphere pressure, Pa ; V_0——air volume of air spring at equilibrum site,m^3 ; m——ploytropic exponent of air, V——air volume of air spring at h displacement site,m^3.

According to equation(2),

$$P=(P_0+P_a)\left(\frac{V_0}{V}\right)^m-P_a \tag{3}$$

Then
$$F=PA=\left[(P_0+P_a)\left(\frac{V_0}{V}\right)^m-P_a\right]A \tag{4}$$

The stiffness of air spring could be defined as

$$\begin{aligned}k_2=\frac{\mathrm{d}F}{\mathrm{d}h}&=\left[(P_0+P_a)\left(\frac{V_0}{V}\right)^m-P_a\right]\frac{\mathrm{d}A}{\mathrm{d}h}\\&-Am(P_0+P_a)\left(\frac{V_0}{V}\right)^m\frac{1}{V}\frac{\mathrm{d}V}{\mathrm{d}h}\end{aligned} \tag{5}$$

According to equation (3),

$$k_2=P\frac{\mathrm{d}A}{\mathrm{d}h}-Am(P+P_a)\frac{1}{V}\frac{\mathrm{d}V}{\mathrm{d}h} \tag{6}$$

From equation(6), it could be found that air spring possess nonlinear and changing stiffness characteristic and its changing value of stiffness is related to air pressure of air spring, effective area of air spring, changing ratio of effective area relative to vertical displacement, air volume of air spring and changing ratio of air volume relative to vertical displacement[8].

Changing course of air spring stiffness is very complex during practical working course and it would be influenced by many factors. If we wanted to describe its changing course accurately, we need to map its mathematics function according to experiment data[2]. For easy to compare, mathematics function mapping stiffness with deformation value was adopted in reference[9].

$$k_2 = 0.787h^2 - 6.929h + 69.72 \tag{7}$$

3. Air Suspension Model of 1/4 Vehicle

Air suspension model of 1/4 vehicle was shown in Figure 1. Dynamic functions were described as follows [10-14]:

$$M_2\ddot{x}_2 + K_2(x_2 - x_1) + C_2(\dot{x}_2 - \dot{x}_1) = 0 \tag{8}$$

$$M_1\ddot{x}_1 - K_2(x_2 - x_1) - C_2(\dot{x}_2 - \dot{x}_1) + K_1(x_1 - q) = 0 \tag{9}$$

$$\ddot{x}_2 = -\frac{1}{M_2}\left[K_2(x_2 - x_1) + C_2(\dot{x}_2 - \dot{x}_1)\right] \tag{10}$$

$$\ddot{x}_1 = \frac{1}{M_1}\left[K_2(x_2 - x_1) + C_2(\dot{x}_2 - \dot{x}_1) - K_1(x_1 - q)\right] \tag{11}$$

M_2——sprung mass, M_1——unsprung mass, K_1——stiffness of tyre；K_2——stiffness of air spring, C_2——damping of air suspension, q——road input, x_1——displacement of unsprung mas, x_2—— displacement of sprung mass.

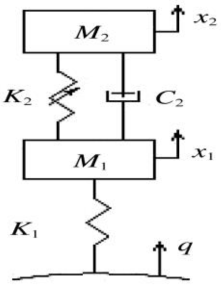


Figure 1. Air Suspension Model of 1/4 Vehicle

According to reference[9], revelant parameters were selected as follows：K_1=3×106 N/m, C_2=8 500 Ns/m, M_1=465 kg, M_2=4250 kg, road input was selected as sine wave, its amplitude, frequency and simulation time were selected as 0.1 m,1 rad/s and 50 s.

According to equation(10) and (11), vibrant acceleration curve of unsprung mass and dynamic load curve of air suspension were shown in Figure 2 and Figure 3.

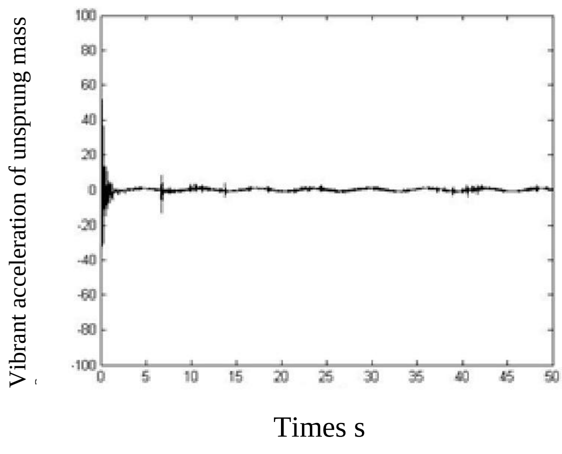


Figure 2. Unsprung Mass Vibrant Acceleration Curve of Air Suspension

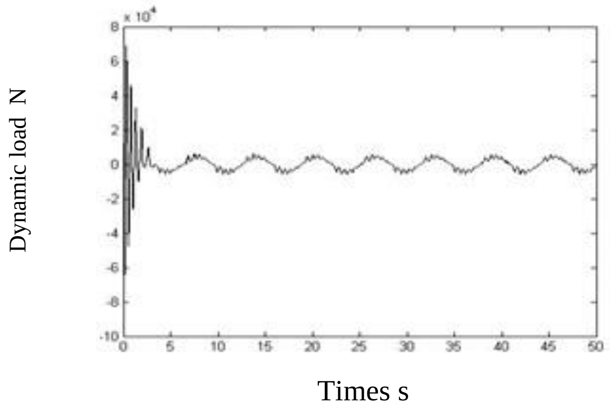


Figure 3. Dynamic Load Curve of Air Suspension

4. Identification based on Elman Neural Network

Elman neural network is a sort of feed-back neural network. Output of hidden layer of Elman neural network will feed-back input of Elman neural network. So network possess ability changed with time and it can effectively reflect dynamic characteristic of dynamic system. Elman neural network consists of input layer, hidden layer, context layer and output layer [15-18]. It was shown in Figure 4 that input layer, hidden layer and output layer were similar with BP neural network. Input layer only transfer signal, output layer can perform linear weighted and the transfer function of hidden layer possess nonlinear characteristic. Compared with BP neural network, Elman neural network adds a context layer and it can feed output of the last moment of hidden layer back to input layer. Adding context layer can enhance processing dynamic information ability of neural network and can better reach goal building dynamic system model.

Elman neural network input layer: $\hat{X}_1(k)$ expresses k moment input of network.

Elman neural network hidden layer: $U(k) = f(w^1\hat{X}_1(k) + w^2U(k-1))$ (12)

$U(k)$ expresses k moment output of hidden layer. $U(k-1)$ expresses $k-1$ moment output of hidden layer. w^1 expresses connection weight from input layer to hidden layer. w^2 expresses connection weight from context layer to hidden layer. S model function $f(x) = 1/\left(1+e^{-x}\right)$ was selected as transfer function.

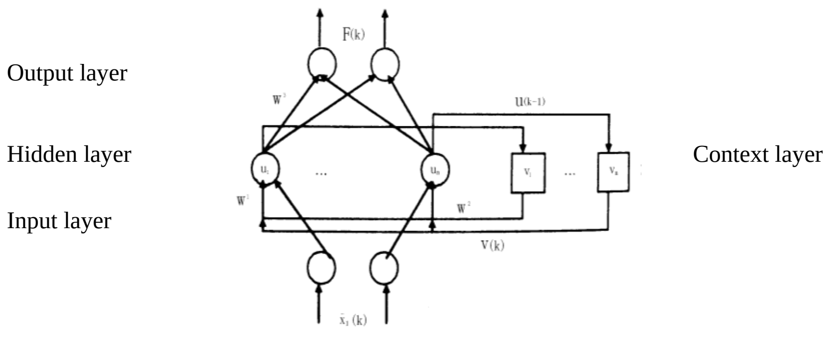


Figure 4. Model of Elman Neural Network

Elman neural network output layer: $F(k) = w^3U(k)$ (13)

$F(k)$ Expresses output of network. w^3 expresses connection weight from hidden layer to output layer.

Errors function of adjusting Elman neural network weight:

$$E(w)=\frac{1}{2}\sum_{k=1}^{n}\left[F_k(w)-\hat{F}_k(w)\right]^2 \tag{14}$$

$F_k(w)$ expresses k moment output of practical system. $\hat{F}_k(w)$ expresses identifying results of Elman neural network. According to gradient descend method, adjusting weight equations could be expressed as follows:

$$\frac{\partial E(w)}{\partial w^3}=-\left[F_k(w)-\hat{F}_k(w)\right]\frac{\partial \hat{F}_k(w)}{\partial w^3}=-e(w)U(k) \tag{15}$$

$$\frac{\partial E(w)}{\partial w^2}=-\left[F_k(w)-\hat{F}_k(w)\right]\frac{\partial \hat{F}_k(w)}{\partial U}\frac{\partial U}{\partial w^2}=-e(w)w^3\sigma(k) \tag{16}$$

$$\frac{\partial E(w)}{\partial w^1}=-\left[F_k(w)-\hat{F}_k(w)\right]\frac{\partial \hat{F}_k(w)}{\partial U}\frac{\partial U}{\partial w^1}=-e(w)w^3\delta(k) \tag{17}$$

$$\sigma(k)=\frac{\partial U}{\partial w^2}=f^{'}\left[U(k-1)+w^2\sigma(k-1)\right] \tag{18}$$

$$\delta(k)=\frac{\partial U}{\partial w^1}=f^{'}\left[\overset{\square}{X}_1(k)+w^2\delta(k-1)\right] \tag{19}$$

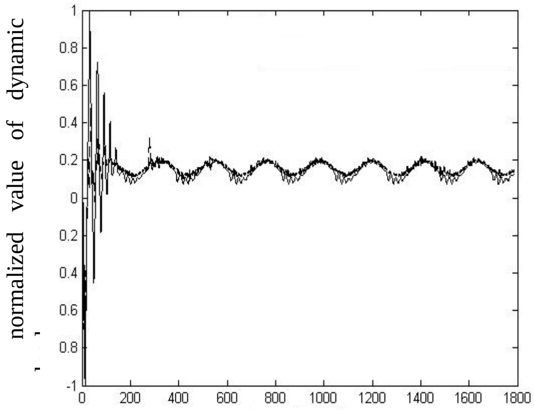
Because hidden function was selected as $f(x)=1/\left(1+e^{-x}\right)$, then

$$\begin{aligned} f^{'}&=-\frac{1}{\left(1+e^{-x}\right)^2}e^{-x}(-1)=\frac{1}{1+e^{-x}}-\frac{1}{\left(1+e^{-x}\right)^2} \\ &=\frac{1}{1+e^{-x}}\left(1-\frac{1}{1+e^{-x}}\right)=f(x)\left(1-f(x)\right) \end{aligned} \tag{20}$$

Equation(18) and (19) are dynamic regression equation. It could be got by initial condition $\sigma(0)=0$ and $\delta(0)=0$. So the weights of Elman neural network could be adjusted acted on the steepest descent method.

5. Identifying Dynamic Load

In this paper, Elman neural network was selected that it consisted of one input layer, one output layer and one hidden layer [20-22]. Input layer consisted of one neuron, hidden layer consisted of 38 S model neurons (Hidden layer node amount was defined according to complicated degree of identifying target and wanted generalization ability. Finally hidden layer node amount was selected as 38 according to results of simulation, comparison and alignment.). Output layer consisted of one linear neuron. In order to improve accurate ratio and generalization ability of identifying results, vibrant acceleration data and dynamic load data must be normalized. Then, vibrant acceleration of unsprung mass was selected as input and dynamic load was selected as output of Elman neural network. Among all input and output data pairs, the 50 data pairs in front were selected as training specimens to train Elman neural network every 200 data pairs. Thereafter, total data of vibrant acceleration were selected as input data of Elman neural network. Identifying results of dynamic load were got by trained Elman neural network. Comparison results of numerical value and identifying value of dynamic load were shown in Figure 4. It indicated that the points which error ratio was smaller than 30% took 75.97%, the points which error ratio was smaller than 20% took 64.48%, the points which error ratio was smaller than 10% took 43.75%. It could find that Elman neural network can effectively identify dynamic load and identifying results can meet demand of intelligent control according under present circumstances.

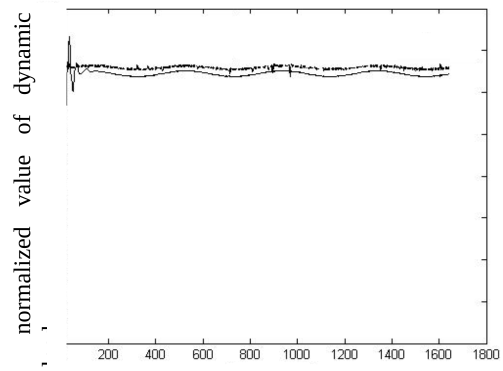


numerical value of dynamic load

--- identifying results of Elman neural network

Figure 4. Comparing Curves of Elman Neural Network and Numerical Values

In order to test generalization ability of Elman neural network, road input was selected as sine wave, its amplitude, frequency and simulation time were selected as 0.05 m,0.5 rad/s and 50 s. vibrant acceleration curve of unsprung mass and dynamic load curve of air suspension were calculated. Vibrant acceleration changed parameters of unsprung mass was selected as input(Maximum and minimum was equal to maximum and minimum of normalized operation in front.). Identifying results of dynamic load were got by trained Elman neural network. Comparison results of numerical value and identifying value of dynamic load were shown in Figure 5. It indicated that the points which error ratio was smaller than 30% took 96.1%, the points which error ratio was smaller than 20% took 95.49%, the points which error ratio was smaller than 10% took 56.27%. It could find that identifying accurate ratio reached higher by trained Elman neural network when input value and output value were smaller than initial value in front. This perhaps owing to less points nearby boundary of maximum and minimum. It indicated that Elman neural network possess better generalization ability under this condition and can map from vibrant acceleration space to dynamic load space.



sampling points

—numerical value of dynamic load

--- identifying results of Elman neural network

Figure 5. Comparing of Elman Neural Network and Numerical Values of Air Suspension Changed Parameter

Road input was selected as sine wave, its amplitude, frequency and simulation time were selected as 0.3 m,2 rad/s and 50 s. vibrant acceleration curve of unsprung mass and dynamic load curve of air suspension were calculated. Vibrant acceleration changed parameters of unsprung mass was selected as input(Maximum and minimum was equal to maximum and minimum of normalized operation in front.). Identifying results of dynamic load were got by trained Elman neural network. Comparison results of numerical value and identifying value of dynamic load were shown in Figure 6. It could find that two curves obviously appeared offset, then gradually approached, and finally stabilized. It could find that identifying accurate ratio reached lower by trained Elman neural network when input value and output value were larger than initial value in front. This perhaps owing to more points exceed boundary of maximum and minimum and numerical value and identifying value of dynamic load obviously appeared offset. Then two curves gradually approached and finally stabilized, it perhaps owing to dynamic adapting ability of Elman neural network.

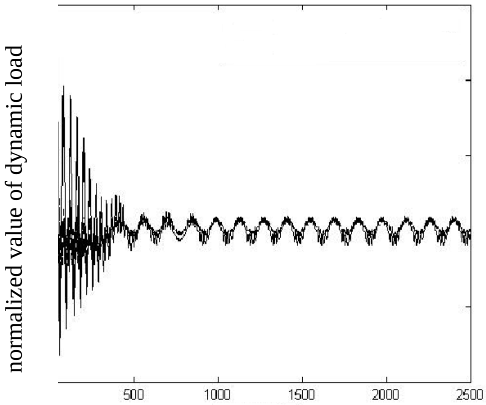


Figure 6. Comparing of Identifying Results of Elman Neural Network and Numerical Values of Air Suspension Changed Parameter

6. Conclusions

(1) Dynamic model of 1/4 vehicle air suspension was established. Vibrant acceleration of unsprung mass and dynamic load was calculated. Vibrant acceleration of unsprung mass was selected as input and dynamic load was selected as output of Elman neural network. Elman neural network was trained by input and output data. Identifying results of dynamic load were got by trained Elman neural network. The points which error ratio was smaller than 30% took 75.97%. It indicated that Elman neural network can identify dynamic load of air suspension.

(2) Vibrant acceleration value and dynamic load value of air suspension were changed to be smaller than initial value in front by changing road input of air suspension. Vibrant acceleration changed parameters of unsprung mass was selected as input. Identifying results of dynamic load were got by trained Elman neural network. Error ratio was smaller than 30% took 96.1%. Identifying accurate ratio reached higher. It indicated that Elman neural network possess better generalization ability under this condition and can map from vibrant acceleration space to dynamic load space.

(3) Vibrant acceleration value and dynamic load value of air suspension were changed to be larger than initial value in front by changing road input of air suspension one more time. Vibrant acceleration changed parameters of unsprung mass was selected as input. Identifying results of dynamic load were got by trained Elman neural network. Because more points exceed boundary of maximum and minimum, identifying accurate ratio

reached lower and two curves obviously appeared offset. Then, two curves gradually approached and finally stabilized owing to dynamic adapting ability of Elman neural network.

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Authors

Bin Yang, he is a Ph.D., associate professor. The main research directions are for the modern design methods. At present, twenty two papers have been published.