Research on Automatic Control System of MR Damper Based on Neural Network Algorithm

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Abstract. The use of MR dampers can achieve the absorption of harmful vibrations such as seismic waves that affect the structure of the building itself. The current control of the MR damper generally uses a pulse width modulation system to control the current input to the MR damper, thereby controlling the MR damper. But this is a semi-automatic control method, and the error is relatively large. This article introduces an MR damper control system that introduces a neural network algorithm. The system uses a half-bridge drive circuit for output current control in the circuit part and uses the Shen BP network algorithm for numerical prediction and fitting. The experimental research and tests conducted in the project show that the use of this fuzzy algorithm can make the MR damper achieve good damping effects under different conditions, and can well improve the original semi-automatic control method.

1. Introduction

At present, the common vibration reduction method used on suspended cable-stayed bridges is to install a damper between the main cable-stayed bridge and the approach bridge to increase the equivalent damping ratio of the cable system, thereby achieving the purpose of vibration reduction. Field experiments of MR dampers have been conducted on the Dong-Ting Lake Bridge in Hunan and the Third Qian-Jiang Bridge in Hangzhou. Both field experiments and calculation simulations show that MR dampers not only have the same superior vibration control characteristics as viscous oil dampers but are also safer Reliable[¹]. The control range of the MR damper for vibration is wider than that of the viscous oil damper. Therefore, the current damping system on cable-stayed bridges mostly uses MR damper as the main damping force generating component[²]. However, the current control method for MR dampers has always been semi-automated, that is, the input current corresponding to the MR dampers under different displacements needs to be manually set. Therefore, in order to solve the semi-automated problem, this paper proposes research on the MR damper automatic control system based on neural network algorithm, in order to solve the problem.

In order to achieve the purpose of predicting the best state of the MR damper at the next moment by reading the instantaneous displacement value and the current state of the MR damper, this project selected the introduction of the BP neural network algorithm as the control algorithm in the automation control system. Both the training samples and the training samples are completed on the PC side. Only
the various node parameters of the trained BP neural network are stored in the embedded microprocessor, and the processor only needs to input and output according to the trained model. Using the predictive ability of the BP neural network algorithm can achieve the effect of accurately controlling the damping force output of the MR damper[3], increase the vibration absorption capacity of the cable-stayed bridge, and increase the service life.

2. Construction of control model based on BP neural network algorithm

In this project, the input quantity that needs to be processed is the instantaneous displacement value $x_0 (mm)$ obtained by the displacement sensor and the PWM wave duty ratio $\eta_1$ corresponding to the current MR damper input current $I_0 (A)$, and the output quantity is the next moment MR The input current $I_{02} (A)$ corresponding to the optimal damping force of the damper corresponds to the PWM wave duty ratio $\eta_2$. According to the above input and output relationship, the BP neural network model can be constructed as shown in Figure 1.

![Figure 1. BP neural network model](image)

2.1. Parameter preprocessing

Since the neural network excitation function used in this project is the sigmoid function, the value of this function is in the range of 0 to 1, so it is necessary to normalize the input and output.

For the two duty cycle type variables $\eta_1$ and $\eta_2$ of input and output, since the duty cycle value ranges from 0 to 1, normalization processing is not required. Therefore, the instantaneous displacement value $x_0$ of the input can be normalized, and the processing method is shown in Formula (1)[4].

$$\bar{x}_0 = x_0 - \mu / \delta$$  \hspace{1cm} (1)

Where $\bar{x}_0$ represents the value of $x_0$ after normalization, $\mu$ is the mean value of $x_0$ in all samples, and $\delta$ is the variance of $x_0$ in all samples.

2.2. Network generation and weight value update

2.2.1. Network initialization

The $n$ samples obtained in the experiment are used as the input of the neuron after preprocessing. For the $j^{th}$ neuron of the input layer, the input is:

$$Net_j = \sum_{i=1}^{n} \mu_{ij} * x_i$$  \hspace{1cm} (2)

Where $Net_j$ represents the net input of the $j^{th}$ neuron, $x_i$ represents the standardized input sample independent variable, $\mu_{ij}$ represents the $i^{th}$ independent variable of the input layer from the input layer to the $j^{th}$ neuron in the hidden layer Enter the weight.
The excitation function \( g(x) \) we used here is the sigmoid function, and its form is:
\[
g(x) = \frac{1}{1 + e^{-x}}
\]  
(3)

2.2.2. Hidden layer and output layer output
Suppose we use a three hidden layer BP neural network, each hidden layer has \( m \) neurons, and the bias from the input layer to the hidden layer is \( a_j \), then the output \( H_j \) of the \( j^{th} \) neuron of each hidden layer is:
\[
H_j = g \left( \sum_{i=1}^{n} u_{ij} \cdot x_i + a_j \right)
\]  
(4)

Further get the output \( O_k \) of the \( k^{th} \) neuron of the output layer:
\[
O_k = \sum_{j=1}^{m} H_j \mu_{jk} + b_k
\]  
(5)

Where \( \mu_{jk} \) represents the output weight from the \( j^{th} \) neuron in the hidden layer to the \( k^{th} \) neuron in the output layer, and \( b_k \) represents the output bias from the hidden layer to the \( k^{th} \) neuron in the output layer.

2.2.3. Update of weight value
The process of solving the BP neural network is essentially constantly updating the weights and biases, so these parameters need to be updated next, and the updated parameters are used for the next training.

First use the sample data to calculate the error, the error value \( e_k \) of the \( k^{th} \) expected output \( \hat{Y}_k \) is:
\[
e_k = \hat{Y}_k - O_k
\]  
(6)

Using the process of error back propagation, the weight update formula is:
\[
u_{ij} = u_{ij} + \rho H_j (1 - H_j) x_j \sum_{k=1}^{l} \mu_{jk} e_k
\]  
(7)

\[
\mu_{jk} = \mu_{jk} + \rho H_j e_k
\]  
(8)

Among them, \( l \) is the number of neurons in the output layer. In this model, only one variable needs to be output, so \( l = 1 \); \( \rho \) is the learning rate of the BP neural network, usually a value between 0-1

2.3. Error detection and iteration stop
When the gradient descent is small or the weights of the neural network are appropriate, the model will eventually move towards the optimal solution. To make the model finally converge, you need to set an end index, such as the algebra of the iteration or the error between the predicted value and the true value. Here we choose to calculate the error loss function to determine whether the iteration can end.

Here, the root mean square error is used to evaluate the prediction accuracy of the model. For \( n \) given samples, the calculation formula is as follows:
\[
e = \sqrt{\frac{1}{l} \sum_{i=1}^{l} (\eta_{2i} - O_i)^2}
\]  
(9)

Among them, \( \eta_{2i} \) is the actual value of the duty ratio \( \eta \) of the \( i^{th} \) sample measured experimentally.
3. System circuit construction

3.1. Main controller system circuit

The main control system circuit includes an embedded microprocessor and its peripheral circuits, sensor acquisition and amplifying circuit, signal output and amplifying circuit three parts, including the sensor acquisition circuit schematic diagram shown in Figure 2.

![](image1.png)

Figure 2. Sensor acquisition and amplification circuit

The displacement sensor converts the collected displacement value (35-65mm) into a current value (4-20ma) through connectors P2 and P3, and then converts it into a voltage value through precision sampling resistors R3 and R4, and uses a Zener diode D3 and D4 perform voltage limiting so that the output voltage does not exceed 2.5V, and then send the signal to the TL082 operational amplifier follower circuit for voltage follow, so that it outputs a stable sampling voltage value, and then uses the embedded microprocessor's own ADC The module performs analog-to-digital conversion and restores the output voltage value to the collected displacement value as the instantaneous displacement input variable $x_0$ of the neural network.

The output signal is an analog voltage value signal. The output analog voltage value signal will be compared with the analog voltage value passed in by the current sensor through the voltage comparator LM311, and the next state will be controlled according to the comparison result whether to continue to provide current to the damper, if it is necessary to continue to provide current to the damper, the optimal duty cycle of the pulse width modulation chip output is calculated according to the above BP neural network algorithm to achieve the purpose of controlling the damper current; if there is no need to continue to provide current to the damper, that is If there is no significant vibration on the bridge surface, the output of the pulse width modulation chip is cut off.

3.2. Drive system circuit

The driving system circuit includes a half-bridge driving circuit composed of two N-channel field-effect transistors KIA75N75, and a field-effect tube driving chip IR2104 and its peripheral circuits. The main circuit composition is shown in Figure 3.[5]

![](image2.png)

Figure 3. Main components of the drive system circuit

The two complementary pulse modulation signals output by the pulse modulation chip in the control system are input to the field-effect tube drive chip IR2104. According to the different input signals, the
drive chip controls the size and flow direction of the current in the field-effect tube half-bridge, thereby controlling MR. The size of the output damping force of the damper and the expansion and contraction direction of the damper.

4. Physical test
The MR damper control system produced by the project team will be used to replace the original MR damper control system on the Tianxingzhou Bridge in Wuhan City, Hubei Province. The maximum damping stroke of the MR damper installed on the Tianxingzhou Bridge is ±200mm. The laser displacement sensor used in the system has a measuring range of ±300mm, so it meets the control requirements of this damper. The physical picture of the MR damper is shown in Figure 4.

Through the previous data test in the field, the MR damper is read by the displacement sensor within a ±200mm stroke, and each 5mm is used as a calibration point, that is, a total of 80 calibration points are measured and calculated to calculate the corresponding damping of the above calibration points. The pulse width value duty ratio \( \eta_1 \) of the pulse width modulation wave input by the driver and the best pulse width value duty ratio \( \eta_2 \) that will be input at the next moment when the calibration point is changed. Repeat the experimental test and take the measured average value of each test point. The BP neural network is trained as the training set of the BP neural network. After the training is completed, the model parameters are imported into the embedded microprocessor, and the physical automatic control test is performed. The physical diagram of the entire system after installation is shown in Figure 5.

At the same time, comparing the vibration displacement \( x_0 \) of the bridge when the MR damper is not turned on, the displacement \( x_1 \) after absorbing the vibration using this automation system and the displacement \( x_2 \) after absorbing the vibration using the original semi-automatic control system, the results are shown in Table 1. (The table only list 7 sets of data), where the calculation formula of vibration absorption rate \( \delta_i \) is:

\[
\delta_i = \frac{(x_0 - x_i)}{x_0} \quad (i = 1,2)
\]

| Vibration displacement of bridge deck \( x_0/\text{mm} \) | Use this automatic system | Use the original semi-automatic system |
|---------------------------------|-----------------|---------------------------------|
| Actual displacement \( x_1/\text{mm} \) | Vibrational absorptivity \( \delta_1/\% \) | Actual displacement \( x_2/\text{mm} \) | Vibrational absorptivity \( \delta_2/\% \) |
| 3.76 | 1.18 | 68.6 | 2.58 | 31.4 |
| 6.92 | 1.93 | 72.1 | 4.37 | 36.9 |
| 4.69 | 1.38 | 70.6 | 2.77 | 41.0 |
| 7.32 | 1.98 | 73.0 | 4.58 | 37.4 |
| 9.14 | 2.77 | 69.7 | 5.88 | 35.7 |
In order to show more intuitively the advantages of this automation system for absorbing bridge vibration, the broken line graph Figure 6. is used to represent the displacement $x_0$ of the bridge deck vibration, the amplitude $x_1$ after the original semi-automatic system is used to absorb the vibration, and the automatic system is used to absorb the vibration. The relationship between the amplitude $x_2$.

![Figure 6. Vibration absorption effect comparison chart](image)

## 5. Summary and conclusion

This paper proposes and introduces a new type of MR damper control system based on neural network algorithm, which includes a software algorithm part, namely BP neural network; at the same time, includes a hardware circuit part, namely embedded microprocessor and damper drive. The real-time data collected by the sensor is transmitted to the BP neural network actuator in the embedded microprocessor for calculation, and the pulse width of the modulation wave corresponding to the best output of the MR damper damping force is obtained and output to the driver, so as to realize the precise automation of the MR damper control. After physical testing of the entire system, the system can meet the requirements of accurately controlling the MR damper. Compared with the original semi-automatic control method, after using the BP neural network algorithm, the BP neural network model can be used to make the damper output. After the damping force, the displacement absorption capacity of the bridge vibration is increased by about 30%. Compared with the cable-stayed bridge that does not add MR dampers to reduce the vibration, the system can absorb about 70% of the displacement caused by the vibration of the cable-stayed bridge.

However, due to the limitation of the number of experiments and conditions on the actual bridge, it is impossible to verify the fitting effect of the BP neural network under more hidden layers, and is restricted by the calculation speed of the embedded microprocessor, it is difficult to integrate more advanced neural network algorithms In the control system, further experiments and adjustments are needed to further improve the ability of the entire damper system to absorb vibration.

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