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Research on Parameter Identification of Bouc-Wen Model of Magnetorheological Damper using Least Square Method

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***Keywords*— Magnetorheological damper, Bouc-Wen model, Least square method, Parameter identification**

***Abstract*— *The Bouc Wen magnetorheological damper model has eight unknown parameters, and the mathematical expression of the model includes the evolution quantity, absolute value term, and exponential term of differential equation, which complicates parameter identification. Researchers in related fields have made numerous attempts to solve the problem that the model's parameter identification method is complex and difficult to implement. A method combining nonlinear least square method is proposed to identify the parameters of the Bouc-Wen model of magnetorheological damper based on the damping characteristics test. Analyze the relationship between the identification parameters and the current and use the curve fitting toolbox to fit the functional relationship. At the same time, use the Simulink toolbox to create a Bouc-Wen simulation model of a magnetorheological damper and select sinusoidal signals with varying current, amplitude, and frequency for simulation and comparison. The Bouc-Wen model is validated using additional amplitude and frequency test data, and the results show a high degree of fit between the test and simulation results. This method can effectively identify the dynamic model's parameters.*

I. INTRODUCTION

Magnetorheological damper is a semi-active intelligent control device with good performance, which has the advantages of not being affected by faults, simple structure, low power consumption, controllable damping force and rapid response [1]. An intelligent control material (magnetorheological fluid) is filled in the magnetorheological damper. Applying the rheological properties of the magnetorheological fluid, the magnetic field strength of the environment where the magnetorheological fluid is located can be adjusted by controlling the current flowing through the copper wire coil wound on the outer wall of the magnetorheological damper, so that the damping force output by the magnetorheological damper can be continuously adjusted within a certain range. Therefore, magnetorheological dampers have been widely used in many control fields such as mechanical vibration reduction and bridge shockproof [2]. However, the MR fluid in the rheological process will undergo shear thinning, which not only makes its damping characteristic curve have nonlinear hysteresis characteristics, but also makes it difficult to establish an accurate, simple, and practical mechanical model of the MR damper [3]. Up to now, there are mainly two kinds of modeling for the damping characteristics of magnetorheological dampers: theoretical modeling and experimental modeling. Due to the gap in establishing a mature theoretical modeling system at this stage, researchers from relevant institutions have invested a lot of research on experimental modeling methods. At present, the common and practical parameterized dynamic models of magnetorheological dampers mainly include Bingham model, double viscous hysteresis model, Bouc Wen model, hyperbolic tangent model, modified Dahl model, phenomenal model, etc. Nonparametric dynamic models mainly include polynomial model, neural network model, differential equation model, etc. [4-5]. Among them, Bouc Wen model can better simulate the nonlinear hysteretic characteristics of dampers, so most scholars at home and abroad use this model in the simulation analysis of practical problems.

The Bouc Wen model of magnetorheological damper contains eight unknown parameters, and the mathematical expression of the model introduces the evolution quantity, absolute value term and exponential term of differential equation, which increases the difficulty of parameter identification. To solve the problem that the parameter identification method of the model is complex and difficult to realize, researchers in related fields have made a lot of attempts. Literature [6] proposed an improved charged system search optimization method to identify the parameters of Bouc Wen model. This method has strong robustness and accuracy and can successfully identify the unknown parameters of highly nonlinear hysteretic systems. However, the optimization mechanism of this method is complex, and too many factors are considered, so it is necessary to search for the optimal solution in the entire data set space; Literature [7] used genetic algorithm to identify the unknown parameters in Bouc Wen model and improved the identification accuracy by gradually narrowing the parameter value range. However, the process has too many iterations, slow identification speed and low efficiency; Literature [8] proposed a method combining genetic algorithm and pattern search method. The advantages of the two methods complement each other and identify the unknown parameters of Bouc Wen model. This method can accurately describe the hysteresis characteristics of magnetorheological damper. However, the accuracy and reliability of the identified parameter data are poor when the excitation amplitude is large; Literature [9] uses the Simulink Design Optimization toolbox in MATLAB software to identify the unknown parameters of Bouc Wen model. Although this method can reduce the complexity of parameter identification process to a certain extent, it also reduces the accuracy of parameter identification; Literature [10] uses unscented Kalman filtering algorithm to identify Bouc Wen model parameters online. This method can ensure the accuracy of parameter identification, but the identification process is cumbersome, the mathematical model is complex, and too many factors are considered. Particle Swarm Optimization (PSO) is an intelligent optimization algorithm proposed in recent years with the rapid development of information industry and the improvement of computer technology. Compared with the above mentioned methods, PSO has the advantages of simple algorithm, fast convergence speed, easy implementation, and strong computing application, which makes it widely concerned in signal processing, multi-objective constrained optimization and other application fields.

The least square method is a parameter identification method to identify the parameters of nonlinear static model based on the least square sum of errors [11]. The nonlinear least squares method has the advantage of high accuracy of parameter identification, but in the actual application process, the optimal solution obtained has a large relationship with the initial value, so the prerequisite for obtaining the optimal solution with high accuracy is to give a good initial value.

Based on the discussion done above, this paper proposes a parameter identification method uses nonlinear least square method based on the Bouc Wen model of magnetorheological damper and damping characteristics test. By analyzing the change trend of the identified parameters with the current, the function relationship is fitted with the help of the curve fitting toolbox. At the same time, the Simulink toolbox is used to build the Bouc Wen simulation model of the magnetorheological damper, and the sinusoidal signals under different currents and other amplitudes and frequencies are selected to verify the universality and accuracy of the parameter identification results through numerical simulation.

II. MAGNETORHEOLOGICAL CHARACTERISTICS AND BOUC WEN MODEL

2.1 Characteristics of Magnetorheological Damper

The mechanical performance of magnetorheological damper is carried out on the tensile test bench [12] . The structural diagram of magnetorheological damper [13] is shown in Figure 1.

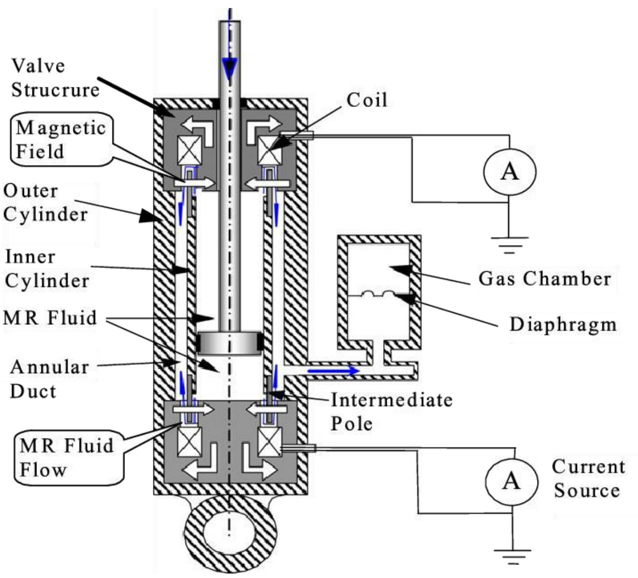

Fig.1: Schematic diagram of magnetorheological damper [13]

The platform uses the different frequency and amplitude signals generated by the vibration exciter and the current provided by the DC power supply for the clamped magnetorheological damper to generate the data changes of damping force, piston rod displacement and other parameters. Where, the excitation signal is a sine signal $x = ASin(2\pi ft)$, amplitude $A = 10mm$, frequency $f = 0.4Hz$, and current intensity is 0, 0.25, 0.50, 0.75, 1.00A respectively. The displacement-damping force and speed-damping force curves obtained from the work diagram and test data processing under various working conditions are shown in Figures 2 to 3.

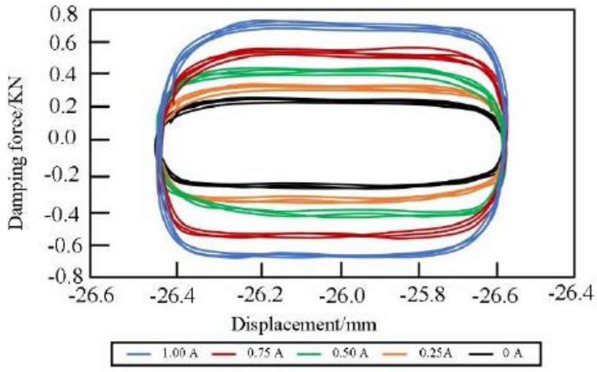

Fig.2: Displacement-damping force curve

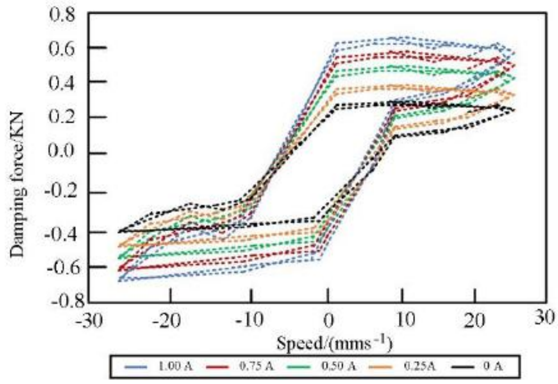

Fig.3: Speed-damping force curve

2.2 Bouc Wen Model of Magnetorheological Damper

Bouc Wen model was proposed by Bouc Wen in 1976. Its structure is shown in Figure 4, which is composed of a hysteretic system, a viscous damping unit and a spring unit in parallel [14].

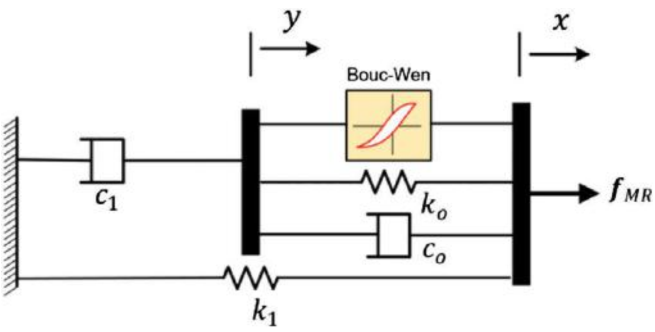

Fig.4: Bouc-wen model structure diagram

This model can better describe the hysteretic characteristics of the damper and considers the advantages of easy numerical processing and strong universality. Its mathematical expression is as follows:

$$\begin{cases} F = c_0\dot{x} + k_0(x - x_0) + \alpha z \\ \dot{z} = -\gamma|\dot{x}|z|z|^{n-1} - \beta\dot{x}|z|^n + A\dot{x} \end{cases} \tag{1}$$

Where: F is the output damping force of the damper, c_0 is the viscosity coefficient of the magnetorheological material after yielding, k_0 is the spring stiffness, x_0 is the initial deformation of the spring, α is the ratio of the yield stiffness to the stiffness before yield, z is the hysteretic displacement, z is the first derivative of the hysteretic displacement, γ is the coefficient affecting the linearity of the transition section, and n is the coefficient affecting the smoothness, β to affect the shape coefficient of the hysteresis loop, A is the amplitude coefficient of the hysteresis loop, x is the displacement of the damper piston rod, and $\dot{x}$ is the velocity of the damper piston rod.

The Bouc Wen model of magnetorheological damper includes c_0, k_0, x_0, α, γ, n, β , A eight unknown parameters need to be optimized and identified. To simplify the difficulty of identification, this paper sets the initial displacement x_0 to 0. In addition, for a specific magnetorheological fluid, the difference of parameter n is not large. The Bouc-Wen model built in the Simulink environment is shown in Figure 5.

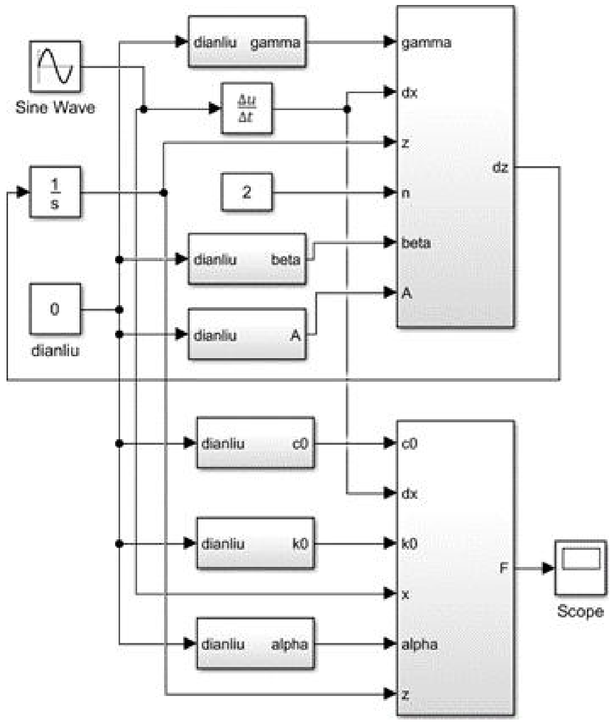

Fig.5: Bouc-Wen model built under Simulink environment

III. PARAMETER IDENTIFICATION

The least square method is a parameter identification method to identify the parameters of nonlinear static model based on the least square sum of errors [15]. The nonlinear least squares method has the advantage of high accuracy of parameter identification, but in the actual application process, the optimal solution obtained has a large relationship with the initial value, so the prerequisite for obtaining the optimal solution with high accuracy is to give a good initial value.

Let the mathematical expression of the identified model be:

$$y = f(x', x'', \cdots, \theta', \theta'', \cdots) \tag{2}$$

Where: y is the output of the system; $x', x'', \cdots$are inputs; $\theta', \theta'', \cdots$ is a parameter. When estimating parameters, the mathematical expression f of the model is known and the data obtained through experiments are $(x_1', x_1'', \cdots, y_1)$, $(x_2', x_2'', \cdots, y_2)$, $(x_n', x_n'', \cdots, y_n)$. The frequency was set to 0.4 Hz o.7 Hz and the current was set to 0.5A for the simulation environment. The input limit is set to 5 and total output was 40 as shown in table 1.

The objective function Q of the sum of squares of nonlinear model errors is

$$Q = \sum_{n=1}^{N} [y_n - f(x_n', x_n'', \cdots, \theta', \theta'', \cdots)]^2 \qquad (3)$$

Bouc-Wen model has eight parameters, and the code of identification methods such as genetic algorithm and particle swarm optimization algorithm is cumbersome and complex. The iterative algorithm based on Matlab least squares method is used to automatically call the iterative algorithm using the test data, so that the test value and the simulation value are infinitely close, and the purpose of identifying all parameters is achieved. The identification flow chart is shown in Figure 6.

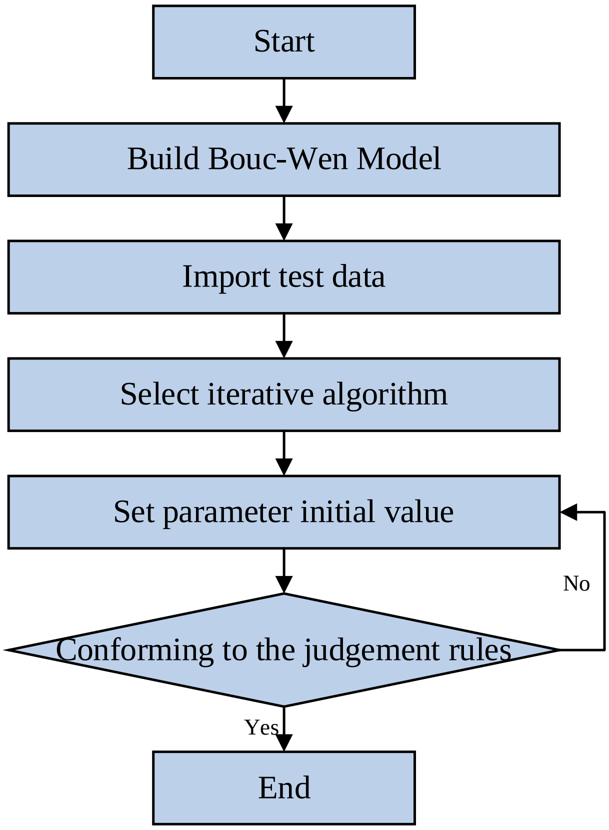

Fig.6: Identification flow chart

Table 1: Identification results of parameters [12]

Current	A	α	β	c_0	γ	k_0	n	x_0
0	1.647	17.5	-889	50	1.4	111.7	1.02	-25.8
0.25	1.626	19.3	-909	50.4	1.24	111.3	1	-25.8
0.5	3.255	19.7	-1048	49.8	1.207	82.4	1.02	-25.6
0.75	3.516	19	-1054	50	1.202	82.3	1	-25.6
1	3.516	19.2	-1060	50	1.196	82.3	1	-25.6

It can be seen from Table 1 that n and x_0 are both approximate constant values, regardless of the test value or the theoretical value, so the average value of n is 1.01, x_0 is -25.64 mm are taken as the initial values for the next parameter identification. Due to parameter A, β, γ is the adjustment coefficient of the hysteretic model. In the pursuit of the minimum sum of squares of errors, A, β, γ compared with α, c_0 and k_0 are easier to adjust. At the same time, it can be found in Table 1 that since the parameter value obtained after the first parameter estimation is used as the initial value of the next parameter estimation, there is an iterative relationship, so A, β, γ the value of k_0 is less affected by the current, which is of more reference significance. Therefore, the parameter identification will be carried out again by using the gradually shrinking boundary method in combination with the data of the last three groups.

Therefore, the next six parameters need to be identified, which reduces the difficulty of identification. Take the parameters identified when the first identification current is 0.5 A as the initial value, and the identification results are shown in Table 2.

Table 2: Identification results for reducing the identification boundary range

Current	A	α	β	c_0	γ	k_0
0	3.49	15.71	-1.02	33.78	1.24	75.04
0.25	3.5	21.4	-1.31	46.08	1.25	68.13
0.5	3.527	27.13	-1.207	49.5	1.207	65.87
0.75	3.502	31.69	-1.232	56.5	1.232	70.87
1	3.52	35.82	-1.25	53.6	1.25	61.65

It can be seen from Table 2 that parameter A, β, γ the variation of k_0 is small, and its average value can be used as the identified parameter of its model, A is 3507.8, β is -1013.6 and γ is 1235.8. α and c_0 change regularly with the change of current, so it can be considered that α and c_0 have the following relationship with current:

$$\begin{cases} \alpha = \alpha_1 + \alpha_2 I \\ c_0 = c_1 I^2 + c_2 I + c_3 \end{cases} \tag{4}$$

IV. MODEL VALIDATION

To verify whether the Bouc-Wen simulation model identified by the nonlinear least squares method can truly describe the damping characteristics of the magnetorheological damper, it is necessary to compare and analyze identification results into the simulation model.

Substitute the above identification results into the simulation model, and first verify the consistency under any current with the same amplitude and frequency. The comparison diagram of displacement-damping force simulation test and speed-damping force simulation test is shown in Figure 7 and Figure 8.

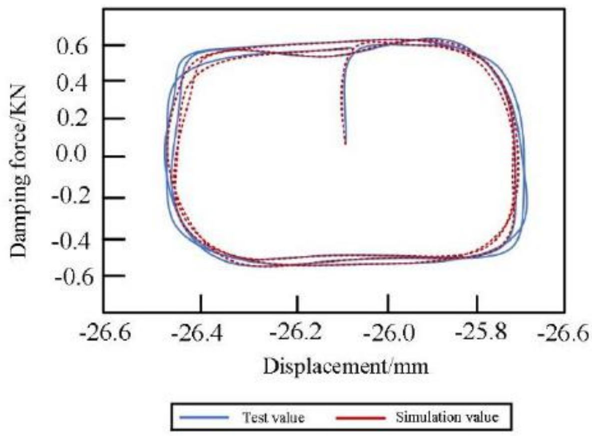

Fig.7: Simulation test at 0.4Hz and 10mm for displacement-damping force

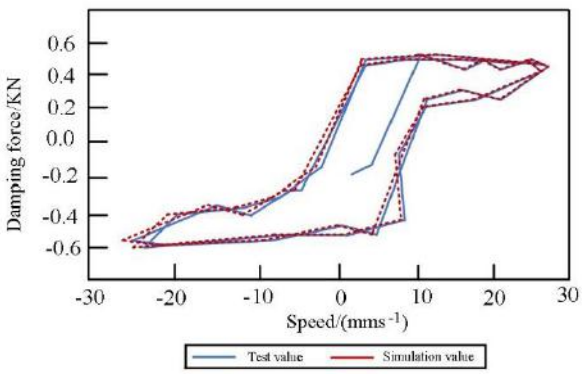

Fig.8: Simulation test at 0.4Hz and 10mm for Speed-damping force

It can be seen from Figure 7 and Figure 8 that the displacement-damping force simulation test diagram and the speed-damping force simulation test diagram are in good agreement, which verifies the correctness of the parameter identification results. To verify the correctness and generality of the least squares method based on the Simulink identification toolbox, data of different amplitude and frequency are randomly selected for verification, as shown in Figure 9 and Figure 10.

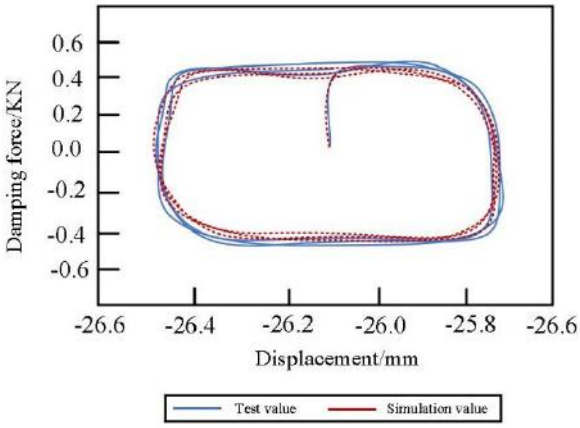

Fig.9: Simulation test at 0.7Hz and 7.5mm for displacement-damping force

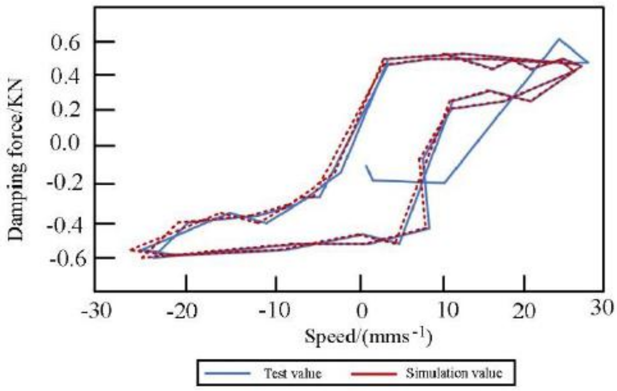

Fig.10: Simulation test at 0.7Hz and 7.5mm for Speed-damping force

It can be seen from Figure 9 and Figure 10 that selecting data of 0.5 A, frequency of 0.7 Hz and amplitude of 7.5 mm for verification can also better reflect the correctness of the identification results and the universality of the dynamic model.

V. CONCLUSION

The Bouc-Wen model's identified parameters can not only be well consistent with the data used in the identification, but they can also better reflect the damper's dynamic properties at various amplitude frequencies. The model's recognized parameters have a clear physical meaning, which is useful for the stabilizer's control task in the following stage. The algorithm is effective and simple to use when applied using the nonlinear least squares method. It can also be used universally for other damper model parameter identification.

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