Inverse Modeling and Optimization of Magnetorheological Damper

Quanmin Guo*1,2
1. School of Mechanical and Precision Instrument Engineering, Xi’an University of Technology, Xi’an 710048, China;
2. School of Electronics Information Engineering, Xi’an Technological University, Xi’an 710021, China
*Corresponding author(E-mail: guoqm@163.com)

Dengxin Hua
School of Mechanical and Precision Instrument Engineering, Xi’an University of Technology, Xi’an 710048, China

Abstract
To eliminate the nonlinear hysteretic characteristic among the output damping force of reverse models of Magnetorheological(MR) Damper, the control current and the relative displacement of pistons, so as to improve generalization and real-time control, back propagation(BP) neural network was used to establish an inverse model of MR damper. The neural network structure, threshold and weight were optimized with genetic algorithm, and the error of predictive current was analyzed. The optimized inverse model was applied to vehicle semi-active suspension control system, and the results showed that: compared with expected current, the control current’s prediction error of inverse model based on BP neural network after optimization was less than that before optimization. After optimization, the vertical acceleration, pitching angular acceleration and roll angle acceleration of suspension decreased, and the real-time control was enhanced.

Key words: Magnetorheological damper, Inverse Model, Nonlinear hysteretic characteristic, Neural network, Genetic algorithm.

1. INTRODUCTION
Magnetorheological(MR) damper (Lijie and Jiong, 2009) is a kind of intelligent damp-adjustable shock absorber with the medium of magnetorheological fluid. Compared with traditional passive dampers, the damping force of MR damper is controlled by input current and the relative displacement of pistons. It is dynamic adjustable with advantages of wide output range, low energy consumption, and fast response. So MR damper has broad prospect of application (Hong and Xun, 2013).

Because MR damper has obvious hysteretic characteristic (Honghui and Jing, 2010), and the model has lots of identification parameters, it is difficult to establish accurate models. Especially in practical application, control current is usually calculated by the desired damping force and relative displacement of pistons. Therefore it is particularly important to establish an inverse model of MR damper. Researchers have done some in-depth research on this aspect. In 1987, Bingham viscoplastic model of magnetorheological damping system was first put forward (Stanway, Sproston and Stevens, 1987). The fitting effect of force-displacement relation was relatively good, but that of force-velocity relation was poor. A differential equation model of MR damper was established, but there were many undetermined parameters, and prone to divergent (Spencer, Dyke and Sain, 1997). A bilinear hysteretic model was put forward to describe the nonlinear response of magnetorheological fluid damper (Yang, Li, and Wang, 2005). The fuzzy theory was applied to conduct effective simulation approximation on forward and inverse models of MR damper. The experimental results showed that this method was feasible, and the forward model had good approximation effect. But complexity of the system would increase if higher accuracy of inverse model was required, and the response time of the system would also increase (Hao and Haiyan, 2006). Back propagation (BP) neural network was used to establish an inverse model of MR damper, which was applied to vehicle suspension control system for simulation (Yingying, Yongjiang and Jinxin, 2011). This method improved the accuracy of the existing model, and improved the suspension performance, but the referred neural network needed to be further optimized. Based on the theory of adaptive neural fuzzy system, non-parametric control system of MR damper was designed. Though there was less calculation, it was still on the stage of forward model research (Ling and Zhongyong, 2011). Considering the damping force as optimization target, the particle swarm algorithm was applied to identify parameters of dampers, and hysteretic characteristic of MR damper was described, providing useful references to parameter selection in reverse model research (Xuuyong, Yu and Hongxin, 2014). The dynamic test data of MR damper was used to build a non-parametric model of MR damper based on Bayesian inference NARX (Non-Linear Autoregressive with Exogenous Inputs) network technology, which improved generalization ability, and achieved real-time and robust intelligent control of MR control system (Zhaohui and Yiqing, 2017).
Considering the difficulty in inverse modeling of MR damper and poor quality control, inverse model of MR damper based on BP neural network was established in this paper, with desired damping force of MR damper and the relative displacement of pistons as input, and the control current as output. To solve the local minima problem in BP neural network, genetic algorithm was used to optimize the structure, threshold and weight of BP neural network, so as to guarantee the global optimality of the training results, and reduce the prediction error of control current of the reverse model.

2. PHENOMENOLOGICAL MODEL AND HYSTERETIC CHARACTERISTIC OF MR DAMPER

By changing the fluidity of magnetorheological fluid in damping channel, MR damper changes the damping coefficient. The characteristic of magnetorheological fluid is associated with magnetic field of different intensity obtained by adjusting the current in excitation coil. The common models of MR dampers include Bingham model, Bouc-Wen model, polynomial model, and Sigmoid model. MR damper phenomenological model based on Bouc-Wen hysteresis operator has given a more accurate description on saturation and nonlinear hysteretic characteristic of MR damper, and it has good commonability. The model consists of three parts: hysteresis operator, multi stiffness and damper, which are combined by series-parallel connection. It can well describe the hysteresis phenomenon of MR damper, and the analytical expression of the phenomenological model is as follows:

\[
\begin{align*}
f &= c_0 \ddot{y} + k_1 (x - x_0) \\
\dot{y} &= \frac{1}{c_0 + c_1} \left[ \alpha z + c_0 \dot{z} + k_0 (x - y) \right] \\
\dot{z} &= -\gamma \dot{y} \left| \dot{z} \right|^{n-1} - \beta \left( \dot{z} - \ddot{y} \right) \left| \dot{z} \right|^n + A \left( \dot{z} - \ddot{y} \right) \\
c_1 &= c_{1a} + c_{1b}i \\
a &= a_a + a_bl
\end{align*}
\]

where \(c_0\) is viscous damping; \(f\) is the output damping force; \(k_0\) is stiffness coefficient; \(c_1\) is viscous damping; \(z\) is evolutionary variable; \(k_1\) is stiffness of accumulator; \(y\) is internal displacement; \(x\) is the relative displacement of the spring; \(x_0\) is initial relative displacement; \(\alpha\) is coefficient scale of Bouc-Wen hysteresis operator; \(\gamma, \beta, A\) mean correlation coefficients for hysteresis characteristics; \(c_{1a}\) and \(c_{1b}\) mean relative parameters of viscous damping; \(a_a\) and \(a_b\) mean constant parameters of coefficient scale \(\alpha\); \(n\) is index coefficient; \(i\) is control current. The parameters are shown in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_0)</td>
<td>997</td>
<td>(a_a)</td>
<td>0</td>
<td>(k_1)</td>
<td>134</td>
<td>(A)</td>
<td>300</td>
</tr>
<tr>
<td>(c_{1a})</td>
<td>8168</td>
<td>(c_{1b})</td>
<td>1723</td>
<td>(x_0)</td>
<td>0.115</td>
<td>(\gamma)</td>
<td>70000</td>
</tr>
<tr>
<td>(c_{1b})</td>
<td>2725</td>
<td>(k_0)</td>
<td>10.72</td>
<td>(\beta)</td>
<td>70000</td>
<td>(n)</td>
<td>2</td>
</tr>
</tbody>
</table>

According to equation (1) and (2), a phenomenological model of MR damper was built. The sinusoidal signal with amplitude of 0.01m and frequency of 2Hz were taken as the relative displacement of pistons, and the control current range was 0-3A. The hysteretic characteristic of the model was analyzed, and the results are shown in Figure 1.

![Graph of damping force and time](image-url)
(b) The relationship between damping force and displacement

(c) The relationship between damping force and velocity

**Figure 1.** Characteristic curve of MR damper phenomenological model under different currents

It can be seen from Figure 1(a) that, when the relative displacement of the piston was constant, the output damping force was increasing with the increase of control current at every moment; when the control current was constant, the output damping force had nonlinear relationship with the time. In each cycle, output damping force were in "yielding" steady state in a short period of time near the peak and valley; Figure 1(b) and (c) showed that the output damping force had obvious hysteretic characteristic against the relative displacement and the speed of piston.

### 3. INVERSE MODEL OF MR DAMPER BY GENETIC ALGORITHM OPTIMIZATION

The semi-active suspension needed to apply the desired adjustment force to vehicle body through MR damper, and form a closed loop feedback to conduct real-time control. This required the establishment of an inverse model of MR damper to predict the current and take it as the control current of MR damper. The output damping force had nonlinear hysteretic characteristic against the damper’s piston displacement and control current, so an inverse model of damping force-current was established by using BP neural network to predict control current corresponding to the expected force.

A three layer neural network was used to build the inverse model of the damper. The input was the expected damping force and relative displacement of the piston, and the output was the control current. In order to reduce the prediction error of the control current, the input values at several successive moments were chosen as the reference input, which means that the control current at a certain time was related to the surrounding input values at this time. 3 values from each of the expected damping force and the relative displacement of pistons near the corresponding moment were selected; for the three layer network, there was an approximate empirical relationship between the number of hidden layer network \( p \) and the number of input \( q \): \( p=2q+1 \). After trial selection in the experiment, it was determined that when there were 18 hidden layers, the effect was the best.
In training phase, white gaussian noise was selected as the control current, and displacement amplitude was 0.01m. 4500 groups of data were collected from each of the input current, piston relative displacement and output damping force for the training of MR damper inverse model based on BP neural network. In prediction stage, in order to illustrate the general adaptation of the inverse model, the sinusoidal signal with amplitude of 3A and frequency of 2Hz was taken as the current control. 500 groups of data were collected from each of relative displacement of pistons, the desired damping force and control current.

The establishment of MR damper inverse model based on BP neural network requires network training, and whether the selection of network structure, initial connection weight and threshold are reasonable directly affects the quality of the network. Moreover, local minima may occur easily in training of BP neural network. In this paper, genetic algorithm was used to optimize the BP neural network to improve accuracy of the inverse model. The idea of genetic algorithm is to simulate the biological evolution process to find the optimal individual, which has strong global optimization ability with little dependence and strong robustness. Inverse model of MR damper requires more samples and multi input, so real number encoding is applied for individual encoding. Each individual is a real number string, and an individual contains all weights and thresholds of the neural network. Variables are encoded into chromosomes for a random population initialization. The predictive current error is taken as the fitness value, and the expression is:

\[ F = \frac{1}{l} \sum_{j=1}^{l} (y_j - y_{id})^2 \]  

where \( F \) is fitness value; \( l \) is the total number of output nodes of neural network; \( y \) is actual output; \( y_{id} \) is ideal output; \( d \) is output node of neural network.

The probability of both crossing and mutation was 0.2. Because real number encoding was applied, so real number crossing method was used. The purpose of crossing was to produce new individuals through gene recombination. The operation method of chromosome crossing is as follows:

\[
\begin{align*}
    a'_{ij} &= a_i (1 - b) + a_j b \quad (a_i, a_j \in [0,1]) \\
    a''_{ij} &= a_i (1 - b) + a_j b \\
    r_{ij} &= \text{random number, and its range is [0,1].} \\
    a_{ij} &= \text{gene No. } j \text{ of chromosome } k; \quad a_{ij} = \text{gene No. } j \text{ of chromosome } l; \quad a'_{ij} = \text{the crossing results of gene } a_{ij}; \quad a''_{ij} = \text{the crossing results of gene } a_{ij}; \quad b = \text{random number, and its range is [0,1].}
\end{align*}
\]

Mutation is the generation of new individuals by altering certain genes on the chromosome, thus avoiding loss of information and maintaining diversity of the population. The method of gene mutation is as follows:

\[
\begin{align*}
    a'_{ij} &= a_{ij} + (a_{max} - a_{min}) \cdot f(g), \quad r \geq 0.5 \\
    a''_{ij} &= a_{ij} + (a_{min} - a_{ij}) \cdot f(g), \quad r < 0.5 \\
    f(g) &= r_{ij} (1 - g / G_{max})^2 \\
\end{align*}
\]

where \( a'_{ij} \) is mutation results of gene \( j \) on chromosome \( i ; a_{max} \) and \( a_{min} \) means the upper bound and lower bound of gene \( a_{ij} ; g \) is the current iteration number; \( G_{max} \) is maximum evolutionary times; \( f(g) \) is a function of the iterations number \( g; r_{ij} \) is random number, and \( g \) is a random number in the range of [0,1].

Through the above process, the optimal initial weights and thresholds of the BP neural network were obtained, and then the prediction accuracy of the MR damper inverse model was improved.

The training sample current was fitted, and the fitting error value of current was analyzed, as shown in Figure 2. the current of the test samples was predicted, and the current error value was analyzed, as shown in Figure 3.

![Figure 2. The curve of fitting current and its error](image-url)
It can be seen from Figure 2 and Figure 3 that results were not good at several regional points, but on the whole, it had good fitting results and test results with low error, showing a higher generalization, and the inverse model needed to be introduced into the semi-active control system for further verification.

4. RESULTS AND ANALYSIS

In order to verify the validity of the MR damper inverse model established in this paper, a control system of 1/4 vehicle semi-active suspension based on MR damper was established by selecting the suspension parameters of a certain vehicle. The inverse model was applied to the control system. As shown in Figure 4, where $M_s$ and $M_u$ are sprung mass and unsprung mass; $x_1$, $x_2$ and $x_3$ are suspension spring mass displacement, unsprung mass displacement and road excitation respectively; $\dot{x}_1$ and $\ddot{x}_1$ are body vertical velocity and vertical acceleration respectively; $f$ is expected damping force of suspension; $i$ is the predictive current of the MR damper inverse model; $F$ is the actual vertical-adjusting damping force of suspension; $x_1-x_2$ is suspension dynamic deflection, i.e. the relative displacement of pistons.

Vibration response occurred when road excitation $x_3$ was given on suspension system. The fuzzy PID controller computed the desired control force $f$ based on the input vertical velocity $\dot{x}_1$ and acceleration $\ddot{x}_1$ of the sprung mass $M_s$. The force and the relative displacement $x_1-x_2$ (piston displacement of the damper) of sprung mass $M_s$ and unsprung mass $M_u$ of suspension system was taken as the input of optimized inverse model of MR damper, then the current $i$ required to generate the desired control force $f$ was obtained. According to the current $i$, MR damper output a damping force $F$ which was close to the desired control force, and acted on the suspension system, thus realizing semi-active control to suppress the vibration of the system.
4.1. Random Road Excitation

White noise was used in road excitation so as to produce the time contour of the road roughness, and its function expression in the time domain is:

\[ \dot{z}(t) = -2\pi f_0 \cdot z(t) + 2\pi \sqrt{G_0} \cdot v \cdot w(t) \]  

(7)

Where \( z(t) \) is the road random excitation; \( v \) is vehicle velocity; \( G_0 \) is the power spectral density of road roughness; \( w(t) \) is white noise. The cut-off frequency \( f_0 = 0.01 \text{Hz} \).

In the case while vehicle is running on road level B condition at constant speed of 20m/s. Body vertical acceleration, suspension dynamic deflection and dynamic tire load were selected as the analysis index. The inverse model and the optimized reverse model were introduced into the control system of 1/4 vehicle semi-active suspension respectively for comparison and analysis. The curves of pavement displacement and suspension performance index are shown in Figure 5, and the comparison of root-mean-square(RMS) of suspension performance index are shown in Table 2.

![Figure 5. The curves of suspension performance index with random road excitation](image)

**Table 2. The comparison of RMS of performance index with random road excitation**

<table>
<thead>
<tr>
<th>Performance Index</th>
<th>Before Optimization</th>
<th>After Optimization</th>
<th>Performance Improvement/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vertical acceleration/m·s⁻²</td>
<td>0.3812</td>
<td>0.3378</td>
<td>11.39</td>
</tr>
<tr>
<td>Dynamic deflection/m</td>
<td>0.0612</td>
<td>0.0523</td>
<td>14.50</td>
</tr>
<tr>
<td>Dynamic tire load/N</td>
<td>1035</td>
<td>676.6</td>
<td>34.63</td>
</tr>
</tbody>
</table>

When the random white noise was taken as road excitation, it can be seen from Figure 5 and Table 2 that: after optimization, body vertical acceleration, suspension dynamic deflection and dynamic tire load were improved by 11.39%, 14.50% and 34.63% respectively. And the dynamic tire load was improved significantly. It is shown that under this road condition, the optimized inverse model of MR damper had much better vibration control effect when it was used in the control system of 1/4 vehicle semi-active suspension.

4.2. Speed Bump Excitation

When vehicles pass trapezoidal speed bump, the body will be impacted. In order to further verify the effectiveness of the optimization method, a cross-sectional model of trapezoidal speed bump were established for analysis, see Figure 6.

![Figure 6. Cross-sectional model of trapezoidal speed bumps](image)
where the height $h$ of trapezoidal speed bump is 0.03m, the bottom width $b$ of trapezoidal speed bump is 0.38m, the projection $d$ of trapezoidal slope on horizontal road is 0.15m. From Figure 8, Trapezoidal profile function can be obtained as shown:

$$y = \begin{cases} 
0.2x + 0.038 & -0.19 \leq x < -0.04 \\
0.03 & -0.04 \leq x < 0.04 \\
-0.2x + 3.8 & 0.04 \leq x < 0.19 
\end{cases} \quad (8)$$

In the case while vehicle is passing trapezoidal speed bumps at speed of 1m/s, the curves of body vertical acceleration, suspension dynamic deflection and dynamic tire load before and after optimization are shown in Figure 6, and the comparison of RMS of suspension performance index are shown in Table 3.

![Figure 6. The curves of suspension performance index with speed bump excitation](image)

<table>
<thead>
<tr>
<th>RMS of performance index</th>
<th>before optimization</th>
<th>after optimization</th>
<th>performance improvement/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>vertical acceleration/m·s²</td>
<td>0.0017</td>
<td>0.0013</td>
<td>23.03</td>
</tr>
<tr>
<td>dynamic deflection/m</td>
<td>0.0122</td>
<td>0.0053</td>
<td>56.56</td>
</tr>
<tr>
<td>dynamic tire load/N</td>
<td>150.8</td>
<td>90.7</td>
<td>39.85</td>
</tr>
</tbody>
</table>

When trapezoidal speed bumps was taken as road excitation, after optimization, body vertical acceleration, suspension dynamic deflection and dynamic tire load of 1/4 vehicle suspension were improved by 23.03%, 56.56%, and 39.85% respectively. And the suspension dynamic deflection and dynamic tire load were improved significantly. Before entering speed bumps, the experiment was disturbed by several weak signals, and there was a slight fluctuation, but basically stable. It can be seen from the figure that the suspension after optimization played a significant inhibitory effect on these small disturbances. When vehicle was passing trapezoidal speed bumps, vibration reduction effect was more obvious after optimization. After leaving speed bumps, the optimized suspension was in steady state in a short time, the response was fast, and the control effect was good, while the suspension before optimization needed a long time to restore the steady state.

From the above comparison result, it can be seen that: when the inverse model of MR damper established in this paper was introduced into the control system of vehicle semi-active suspension, all the three performance indexes of semi-active suspension have been greatly improved whether Random road excitation or speed bump excitation, and effectively improves the ride comfort. This showed that the suspension performance could be further improved after optimization, and verified the feasibility and effectiveness of the genetic algorithm.
5. CONCLUSIONS

1) This paper presents an inverse model of MR damper based on BP neural network optimized by genetic algorithm. After optimizing BP neural network structure, threshold and weight with genetic algorithm, the inverse model has more accurately described the hysteretic characteristic of MR damper inverse model, and the local minima problem of the conventional inverse model in predicting current was solved. Thus, the inverse model proposed in this paper has more accurate prediction on the expected control current.

2) Sinusoidal wave was taken as input to conduct sample fitting on control current. Generally, the fitting was good; error of predictive current was small; the fitting value was close to the actual value of samples; step jump errors occurred in the individual scattered areas.

3) From error analysis and control effect, it has verified the effectiveness of genetic algorithm in optimizing the inverse model of MR damper based on BP neural network. In sampling, white gaussian noise was selected as input. The fitting precision was not very high due to the large number of samples and great value range. Subsequently, various indicators can be independently analyzed, and further research can be conducted with different road input.

ACKNOWLEDGEMENTS

This research is supported by Shaanxi province natural science foundation research project (No. 2014JM2-6112) and Natural Science Foundation of Shaanxi Provincial Department of Education (No.14JK1342).

REFERENCES