**Nonparametric modeling of magnetorheological elastomer base isolator based on artificial neural network optimized by ant colony algorithm**

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**Abstract**

Laminated magneto-rheological elastomer (MRE) base isolator is regarded as one of the most promising candidates for realizing adaptive base isolation for civil structures. However, the intrinsic hysteretic and nonlinear behavior of MRE base isolators imposes challenge for adopting the device to accomplish high-accuracy performance in structural control. Therefore, it is essential to develop an accurate model for symbolizing this unique characteristic before designing a feedback controller. So far, some classical parametric models, such as Bouc-Wen, Dahl and LuGre, have been proposed to depict the hysteretic response of MR devices, i.e. MR damper, which may also be used for describing the nonlinear behavior of MRE base isolator. However, the parameter identification is difficult to implement due to the nonlinear differential equations existing in these models. Considering this problem, this paper proposes a nonparametric model, i.e. an artificial neural network (ANN) based model with three input neurons, eighteen hidden neurons and one output neuron, to predict the MRE isolator behavior. In this model, the ant colony algorithm is employed for model training to obtain the optimal weights based on the force-displacement/velocity data sampled from the MRE isolator. Finally, experimental data are used to validate the effectiveness of the proposed ANN based model with the good forecasting results.

**Keywords**

Magneto-rheological elastomer, base isolator, modeling, artificial neural network, ant colony algorithm

**Introduction**

Magneto-rheological elastomer (MRE), as a type of intelligent material, is made up of micro-sized magnetic particles dispersed in the elastomeric rubber medium. When an external magnetic field is applied to the composite, the MRE exhibits great property variation such as shear modulus and damping (Shen Y et al., 2004; Nehrooz M et al., 2014). MRE has demonstrated to be effective in vibration control of structures and MRE base isolator has been proposed as the adjustable semi-active constituent in the base isolation system due to its fast response, controllable stiffness and low power requirement. Recently, a full-scale base isolator was designed with 47 layers of MREs, in which the stiffness increases around 38% (Li Y et al., 2013a).

The major role of MRE base isolator in a base isolation system is to isolate the dangerous vibration or shock contents from the structures. By identifying the characteristics of incoming earthquakes and analyzing the structural responses, MRE base isolation system can adjust its property to avoid resonance thus protecting the building with the help of control system. To fully take advantage of unique features of MRE base isolator, an effective and robust MRE isolator model is required for the design of a base isolation control system. Although several studies have been conducted for this purpose, problems and difficulties still exist since depicting the hysteretic and nonlinear behaviors of the MRE isolator is a challenging task. Up to present, some parametric models are available for modeling the MRE isolator, including Bouc-Wen model (Yang J et al., 2013), improved Dahl model (Yu Y et al., 2014c), LuGre friction model (Yang F et al., 2014), hyperbolic hysteretic model (Yu Y et al., 2014b) and strain stiffening model (Li Y et al., 2014; Yu Y et al., 2014a). Although they are sufficiently to describe the hysteretic responses, the nonlinear differential equations in these models may hinder the realization of the feasible control system due to the computational needs. Besides, this type of models is largely dependent on the initial structure and parameters of the model. If the initial values are misplaced, the robustness of the control system will be deteriorated.[[1]](#footnote-1)

Artificial neural network (ANN) is an effective modeling method capable of dealing with linear and nonlinear multi-variable regression problem, which is not able to be solved by a mathematical model (Lu Y et al., 2008; Lee J and Kim S, 2007). The major benefit of ANN is that it does not require the specific information of the physical parameters of the systems but utilizes the limited experimental samples to forecast the relationship between the input and output variables. To date, the study on ANN model of MRE isolator has not been reported yet.

The main issue existing in the applications of ANN is its vulnerability in falling into the local optimum. Because of the complex characteristic of network training, the simple function can also lead to a very complicated error surface. As a result, the performance of an ANN on forecasting the outputs is highly dependent on the selection of initial weights. Even if the initial weights are assigned in a limited scale, the local optimum, which may not be the global optimal solution, is still inevitable. This local optimum brings serious consequences when ANNs are utilized in practical applications. To overcome this problem, several approaches have been presented for optimal ANN parameters. The most common method is to modify existing local search algorithm such as cascade correlation and decremental algorithms. However, these algorithms cannot completely guarantee the global optimal solution. Another method is to adopt the global searching algorithm such as simulated annealing, evolutionary programming and ant colony algorithm (ACA). Among these algorithms, ACA is a recently prevalent global searching algorithm owing to its perfect performance in solving optimization problems (Dorigo M et al., 1996). So far, the ACA has successfully applied to the non-deterministic polynomial (NP) hard problems such as quadratic assignment, scheduling, vehicle routing and travelling salesman problems (TSP).

In this study, an ant colony optimized ANN is proposed to model MRE isolator behaviors. First, ACA is introduced to select the proper connection weights of ANN. Then, the ANN is trained to explore the specific relationship between loading conditions and shear force of the isolator. The trial and error approach is also employed to confirm the configuration of the network. The forecast results acquired by the network model are compared with the real testing results as well as the predictions by other conventional models. Finally, the effects of different loading parameters on the responses of MRE isolator are also investigated.

**Experimental system and testing**

Experimental tests are carried out with a new MRE base isolator, shown in Figure 1. This device is composed of several important elements such as laminated MRE layers and steel core, electromagnetic coil, cylindrical steel yoke and connecting plates. The laminated structure is to guarantee the strong loading capacity in vertical direction and low lateral stiffness in horizontal direction. Electromagnetic coil is to energize the MRE material in the core with sufficient magnetic field. Top and bottom plates are to connect the device with ground and superstructure. In the device, soft MRE samples are used to achieve maximum MR effect. Detailed introduction on the device can be found in reference (Li Y et al., 2013b).

In the cycling testing, various sinusoidal inputs with controllable displacements are selected to load the device. In this work, amplitudes of 2mm, 4mm and 8mm are chosen under the loading frequencies of 0.1Hz, 1Hz, 2Hz and 4Hz. In each loading condition, four current levels (0A, 1A, 2A and 3A) corresponding to different magnetic fields are used to evaluate the ability of the MRE isolator. More than 10 cycles of sampling data are measured so that the sampling signals in a stable condition can be obtained. The sampling frequency for data acquisition is 256Hz.



**Figure 1.** Structure of MRE base isolator

MRE: magnetorheological elastomer

**Neural network modeling for MRE isolator**

In this work, an available neural network toolbox v.8.0 (Matlab v.2012b, The Mathworks, Inc.) is utilized to build the network model for forecasting the behaviors of the MRE base isolator. General ANN is a multi-layer network composed of connected neurons in input, hidden and output layers. To train an ANN model, the numbers of neuron in each layer as well as the transfer functions between layers are required in advance. In this study, the displacement and velocity of the isolator together with the applied current are used as the input variables in the network, and the shear force of the loaded isolator is regarded as the output of the network. The number of neurons in the hidden layer is mainly dependent on accuracy requirement of the practical problem to be tackled. Here, the trial and error approach is used to determine the optimal neuron number of the hidden layer. Furthermore, the log-sigmoid function is adopted as the transfer function in the network to connect the neurons in different layers. The log-sigmoid function provides an output between 0 and 1, and its expression *f*(*x*) is described as:

 (1)

The training of an ANN is an optimized iteration process, which usually uses back propagation (BP) algorithm to adjust the connecting weights for an optimal performance. However, as the conventional disadvantage in ANN, the BP-NN is easily fallen into the local optimum, which may be not the global optimum. This is mainly because the solution is highly relied on the randomly selected connecting weights. Besides, if the network is too complicated, considerable computational effort is required for network training by the propagation method. Therefore, it is important to find a reliable approach to optimize the connecting weights in ANN.

**Ant colony algorithm-based neural network**

Ant colony algorithm was first presented by Dorigo et al. (1996) as a multi-agent method to deal with the complicated combinatorial optimization. Inspired by the behavior of ant swarm to search the food, the ACA has successfully applied to the solution of NP hard problems such as quadratic assignment, scheduling, vehicle routing and travelling salesman problems (TSP). In this study, the ACA is utilized to optimize the connection weights to prevent the network from falling into the local optimum. The detailed process of ACA-optimized ANN (ACA\_ANN) can be illustrated as follows:

Suppose there are *m* weights to be optimized in the network, denoted as *p*1, *p*2, …, *pm*. For an arbitrary *pi*, a corresponding set *Ipi* with *N* random nonzero values is constructed. Each ant starts from the first set (*Ip*1) and randomly selects an element in *Ipi* according to its artificial pheromone. After element selection in all sets, the ants arrive at the food source, and then go back the nest in the same way and the pheromone of the selected elements are adjusted in the meantime. Repeat this process until all ants converge to the same path, which means that the optimal parameters of ANN are obtained.

**Step 1.** Initialize the parameters. Initially, all elements in *Ipi* are assigned the same values of pheromone:, *1*≤*j*≤*N*. Set ant number *S*, iteration number *Nc*=0 and maximal iteration number *Nmax* as the termination condition.

**Step 2.** Release all ants. Each ant randomly selects an element in each set *Ipi* (1≤*i*≤*m*) according to the following probability *P*:

 (2)

where denotes the remaining pheromone of *j*th element in set *Ipi* by *k*th ant.

**Step 3.** Repeat Step 2, when all the ants finish the element selection in all sets, calculate the error between the expected value and real output of the network calculated by weights selected by each ant: *,* where *On* and *Oq* denote the real and expected outputs of the network, respectively. If *δ* is smaller than the expectation error *ζ*, record and store the current weights; otherwise, *Nc*=*Nc*+1, *t*=*t*+*m*, and update the pheromone of each element in all sets *Ipi* (1≤*i*≤*m*) according to the following equation:

 (3)

where *ρ* (0≤*ρ*≤1) is the residual factor and 1-*ρ* denotes the evaporation degree of the pheromone between time *t* and *t*+*m*; denotes the pheromone placed at element in set *Ipi* by *k*th ant, and when element *j* in *Ipi* is selected by ant *k*; otherwise, . In the above expression, *Q* denotes the total pheromone which is a constant for the tuning purpose, and *Q* is set as 30 in this work. *Lk* denotes the maximal training error of the network with connection weights selected by *k*th ant, defined as:

 (4)

where *h* denotes the sample number.

**Step 4.** Repeat Steps 2 and 3 until the termination condition is satisfied, that is *Nc*≥*Nmax*. Meanwhile, the algorithm stops and outputs the optimal network weights.

The procedure of ACA to optimize ANN can be described in Figure 2.



**Figure 2.** Algorithm Procedure

**Modeling results and analysis**

*Data set selection*

Experimental data is used to train the ACA\_ANN model of MRE base isolator and to examine the model afterwards. In this work, two cycles of samples gained from the tests in all conditions are selected and divided into two groups: training samples (one cycle) and testing samples (one cycle). To avoid the effect of different sample dimension as well as overflows, both training and testing samples are normalized in the range of [0, 1] according to the following equation:

 (5)

where *xi* is the *i*th raw data, and *xmax* and *xmin* denote the maximal and minimal values of the sample set, respectively.

*Model and algorithm parameters setting*

*ANN parameters*. The network configuration and algorithm parameters are significant to the performance of trained ACA\_ANN model. In this part, an optimal structure of model is determined first according to the fixed ACA parameters. The initial parameters of ACA algorithm is set as: the ant number is 20, the iteration number is 300 and the residual factor is 0.5. Then, the optimal values of algorithm parameters are obtained in accordance with assured network structure. Here, a multi-layer perception network is considered with three input neurons (displacement, velocity and current) and one output (shear force). The only uncertainty is the number of hidden layers as well as the neuron number in each hidden layer. Related studies show that the optimal neuron number in hidden layer can be obtained by the following equation (Lee J and Kim S, 2007):

 (6)

where *β* is a constant in the range of [1, 10], *nin* and *no* denote the neuron numbers in input and output layers, respectively. In this case, the range of neuron number of each hidden layer in the ANN is obtained: [3, 12]. The trial and error method is used to select the optimal neuron numbers by evaluating the mean square error (MSE).

Figure 3 describes the MSE errors of ANN models for different network configurations. It is obviously observed that one hidden layer model always has a higher MSE index than the others. However, there is almost no difference between two and three hidden layers when the neuron number is larger than 5. Therefore, the network configuration of two hidden layers is selected and the optimal choice is 9 neurons in each hidden layers according to Figure 3.

*Ant number*. Based on the above analysis, the optimal ACA\_ANN configuration to model the MRE base isolator is (3, 9, 9, 1), depicted in Figure 4. In the following, the optimal values of ACA parameters are determined by analyzing MSE errors according to above network structure. Figure 5 shows the influence of ant number on the model error and training time when the iteration number is 300 and the residual factor is 0.5. In this work, the performance of the model is evaluated using 5, 10, 15, 20, 25 and 30 ants. For the given training samples, it is obvious that the model has lowest error for 20, 25 and 30 ants but the increase of ant number will lead to higher training time. Thus the value of ant number is selected as 20.



**Figure 3.** MSE in the ACA\_ANN models with different hidden layers.

MSE: mean square error

*Iteration number*. Likewise, the iteration number is another important parameter related to the network performance. Generally, adding the iteration number will cause the tremendous runtime of ACA algorithm whilst less iteration will restrain the ants to search for more possible states, resulting in the premature convergence. Figure 6 demonstrates the effect of iteration number on model performance and time consummation. It is clearly seen that the model arrives at its optimal solution when 300 times’ iterations are adopted in every step of ants.



**Figure 4.** Network configuration for MRE isolator model

MRE: magnetorheological elastomer

*Residual factor*. After determining the ant number and iteration number, the effect of the residual factor on network performance is also studied. The residual factor usually guarantees the ants to keep a good cooperation through adjusting pheromone. When the value of *ρ* is increased, the remaining pheromone will guide the following ants with more desirability, which may force the ants to select the feature not selected before. On the contrary, if the value of *ρ* is too small, it will cause less pheromone remaining on the feature of producing good subsets, making the ants non-cooperative and thus resulting in poor performance. In this work, ACA\_ANN with the residual factor of 0.1, 0.3, 0.5, 0.7 and 0.9 are analyzed, when the ant number is 20 and the iteration number is 300. Figure 7 depicts the performance of ACA\_ANN with different residual factor values. The result shows that the optimal value of the residual factor is 0.3.



**Figure 5.** Influence of ant number on performance of ANN

ANN: artificial neural network



**Figure 6.** Influence of iteration number on performance of ANN

ANN: artificial neural network



**Figure 7.** Influence of *ρ* on performance of ANN

ANN: artificial neural network

*Modeling results*

On basis of the optimal algorithm parameters and network structure, an effective and robust ACA\_ANN model is constructed. The testing samples are inputted into this trained model to evaluate its performance on forecasting the responses of MRE isolator. Figure 8 gives the comparison between predicted responses and training samples when loading the device with 4Hz frequency excitations. It can be seen from the figure that the predicted values from the ACA\_ANN model provide the perfect agreement with the testing data.



**Figure 8.** Predicted values vs. testing samples

To further illustrate the capacity of the proposed ACA\_ANN model to forecast the hysteretic behaviors of MRE base isolator, several groups of comparisons between testing and predicted responses are performed under different loading conditions. Figure 9 shows the experimental and predicted responses between shear force and displacement/velocity under 4 Hz frequencies, three amplitudes (2mm, 4mm and 8mm) excitations with current of 2A. It is obvious that the proposed ACA\_ANN model can well capture the variation of stiffness, damping and hysteresis of MRE base isolator with different amplitude excitations. Figure 10 exhibits the compared force-displacement/ velocity responses via driving the device with the 4Hz frequency, 8mm amplitude excitations under 0A, 1A, 2A and 3A currents. The comparison shows that the effective stiffness will ascend with the increase of the applied current. The proposed model not only can better portray this phenomenon but also can depict the increasing nonlinearity in force-velocity responses. Figure 11 provides the influence of varying frequency on the property of the device. From this figure, it is obvious that the excitation frequency has a little effect on the effective stiffness as well as the maximal shear force. Especially, in the condition of the frequency larger than 0.1Hz, the effective stiffness and shear force almost keep unchanged with the ascending frequency. Different from the force-displacement responses, the increase of excitation frequency l results in the growing nonlinearity of the force-velocity relationship. And the proposed model is able to effectively depict this characteristic.

In order to study the superiority of ANN model optimized by ACA, another multi-layer ANN model is designed. For the purpose of fair evaluation, the structure of this model is completely same as that of proposed ACA\_ANN model. The only difference is that this model adopts the Levenberg-Marquardt (LM) training algorithm to optimize the values of connecting weights. Figure 12 illustrates the regression analysis between experimental and predicted values. In the figure, the solid line means the good fitting curve and *R* denotes the correlation coefficient between predicted values and target outputs. It can be seen from Figure 12 that the results from ACA\_ANN model, with *R* of 0.9987, display a better agreement between predicted and real values than LM\_ANN model, which corresponds to *R* of 0.9818.

 

(a) Force-displacement responses (b) Force-velocity responses

**Figure 9.** Comparison between testing and predicted responses by ACA\_ANN model (4Hz-2A)

 

(a) Force-displacement responses (b) Force-velocity responses

**Figure 10.** Comparison between testing and predicted responses by ACA\_ANN model (4Hz-8mm)

 

(a) Force-displacement responses (b) Force-velocity responses

**Figure 11.** Comparison between testing and predicted responses by ACA\_ANN model (3A-4mm)

*Model performance comparison*

To elaborate the effectiveness of the proposed ACA\_ANN model, a comparative study is conducted with several classical MRE device models: Bouc-Wen model, improved Dahl model, LuGre model, hyperbolic hysteretic model and strain stiffening model. To build a fair comparison, all the models are tested with the same sampling data (4Hz-2A-8mm). And particle swam optimization (PSO) is also used for model parameter identification. In this case, the algorithm parameters of PSO are set as: the inertia weight factor *w*=0.7298, the acceleration coefficients *c*1=*c*2=1.4962, the particle number *Nps*o=50 and the maximal iteration *Nmax\_pso*=400. Figure 13 gives the comparison between experimental data and predicted responses from six MRE isolator models. The results show that the proposed ACA\_ANN model provides the optimal prediction capacity. Although other models are able to better describe the hysteretic and varying features of the device, some imperfections still exists in some important regions. Especially in the peak force regions, the modeling error becomes more obvious.

 

(a) Results from LM\_ANN model (b) Results from ACA\_ANN model

**Figure 12.** Regression analysis

 

(a) Bouc-Wen model (b) Improved Dahl model

 

(c) LuGre model (d) Hyperbolic hysteretic model

 

(e) String stiffening model (f) ACA\_ANN model

**Figure 13.** Prediction comparison for different MRE isolator models

MRE: magnetorheological elastomer

The relative error distribution between measuring and predicted forces from six models is illustrated in Figure 14. Due to the higher-degree nonlinear differential equations in the parametric models, the larger relative error distributions are noted from the predicted forces. For another, the relative error distribution found in the ACA\_ANN model is much smaller than that of others because of its optimal network configuration. Table 1 gives the running time for six models. It is noticeable that compared with hyperbolic hysteretic and ACA\_ANN models, the others always require the longer running time for model parameter identification. It is mainly because these models have highly nonlinear differential equations in their expressions, which are difficult to be solved. The hyperbolic hysteretic model is relative simple without any differential equation and just requires least amount of time for model identification among six models. However, its relative error is larger than others, illustrated in Figure 14. On the whole, the proposed ACA\_ANN model is superior to other classical models in model accuracy and running time.



**Figure 14.** Relative error distribution of six MRE device models

MRE: magnetorheological elastomer

**Table 1.** Running time for different models

|  |  |
| --- | --- |
| Model | Running time (s) |
| Bouc-Wen | 153.7362 |
| Improved Dahl | 138.1516 |
| LuGre | 149.0261 |
| Hyperbolic hysteretic | 68.5554 |
| String stiffening | 243.1591 |
| ACA\_ANN | 76.3915 |

**Conclusion**

A novel nonparametric model based on artificial neural network (ANN) is presented to describe the nonlinear characteristic of magneto-rheological elastomer (MRE) base isolator. Comparing with traditional parametric models, the newly proposed model doesn’t require predicting the model structure and initial values of model parameters, thus having high robustness and modeling accuracy. In order to enhance the forecast capacity of ANN model, an ant colony algorithm is adopted to optimize the connecting weights in the network. To demonstrate the ability of the proposed model, experimental measurements from MRE base isolator are utilized to train and test this model. Testing results indicate that the proposed model has a perfect capacity for forecasting the hysteretic responses of MRE base isolator under various loading conditions. Moreover, an ANN model optimized by Levenberg-Marquardt (LM) algorithm as well as five classical MRE device models is introduced to make the performance comparison with the newly proposed model. Both comparison results are included to illustrate the effectiveness and superiority of the proposed model in modeling MRE isolator.

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