AMSE JOURNALS-AMSE IIETA publication-2017-Series: Modelling A; Vol. 90; N°1; pp 44-57
Submitted Jan. 2017; Revised March 15, 2017, Accepted April 15, 2017

Optimal Control of SMA Cables System Based on Genetic Optimized BP Neural Network Constitutive Model

Zhou Yuan*,*** , Wang Deli** ,Wang Sheliang***, Wang Juan*

*College of Science, Chang'an University, Xi'an, 710061, China (1426673867@qq.com).

**Taizhou city urban and rural planning design and research institute, Taizhou, 318000, China.

***College of civil engineering, Xi'an University of Architecture & Technology, Xi'an, 710055, China.

Abstract

This paper firstly measures the super-elasticity of SMA through the mechanical property test of austenite SMA wire. On the basis of the SMA material property test, it establishes a genetic optimized BP network constitutive model for SMA by considering the effect of loading/unloading rate on the mechanical properties of SMA, and using the experimental data as the training data of neural network. Then, the author processes the constitutive model in MATLAB, uses the improved genetic algorithm to optimize the location and number of SMA in a spatial model structure, and makes seismic response analysis of the optimal configuration. The results show that: the prediction curve of the genetic optimized BP network constitutive model is better agreement with the experimental curve and more stable than that of non-optimized BP network; the BP network constitutive model is easy to invoke, high in precision and beneficial to the MATLAB simulation analysis of SMA control system. Moreover, optimized by the genetic algorithm, the SMA control system can more effectively reduce the seismic response of the structure. For example, the seismic response of the controlled structure is lower than that of the uncontrolled structure by more than 15%, and the control effect of the interlayer displacement response of the structure is more obvious than that of the acceleration response.

Keywords

SMA mechanical tests, BP network, Optimized BP network constitutive model, MATLAB simulation, Seismic response

1. Introduction

As an excellent smart metal sensing and actuating material, shape memory alloy (SMA) boasts such two unique features as shape memory effect and super-elasticity and advantages like high damping, fatigue resistance, corrosion resistance, etc. Thus, the SMA is a favorite choice of civil engineers [1-6]. The constitutive model is the basis of the theoretical analysis and experimental study of SMA. However, it is very difficult to establish an accurate mathematic constitutive model due to the large variability of mechanical properties and the presence of numerous external influencing factors. Major progress had not taken place until Muller et al. proposed a SMA constitutive model in late 1970s. Since then, researchers have come up with various SMA constitutive models based on material property tests [7-9]. The constitutive model is a one–dimensional strain-gradient continuum model of an SMA wire element, including two internal field variables, possible unstable mechanical behavior, and the relevant thermo-mechanical couplings resulting from latent heat effects [10]; Zhu proposed a new model which was recoverable shape memory Strain during different phase transformation, reflect the action of martensite reorientation and overcome the defect of Tanaka's model when the SMAs' microstructure was fully martensite [11]; Zhou and Liu establish a precise constitutive model which includes the equations describing the phase transformation behaviors and thermo-mechanical processes of shape memory alloy [12]; Thamburaja and Nikabdullah develop a non-local and thermo-mechanically-coupled constitutive model for poly-crystalline shape-memory alloys (SMAs) capable of undergoing austenite martensite phase transformations [13] ; The most widely used SMA constitutive model is the Brinson constitutive model, a phenomenological constitutive model featuring thermodynamics constitutive relation and plasticity theory [14-15]. All of the above constitutive models have apparent limitations because they simulate the mechanical behavior of the material by mathematical methods. There are many factors influencing the constitutive curve of composite materials similar to SMA. It is impossible to establish an accurate mathematical model to express the effect of factors on the constitutive model, leaving artificial simplification and approximation as the only options. In recent years, intelligent algorithms are playing an increasingly important role in building constitutive models of materials. As a nonlinear modeling method, the artificial neural network intelligent algorithm does not need to predict the constitutive form of material, and can intelligently analyze the influence degree of each influencing factor on the constitutive equation, thereby creating a favorable condition for the establishment of a precise constitutive model [16-17]. However, the results of artificial neural network are greatly affected by variation in the initial threshold and the weight of the neuron. Therefore, it is necessary to optimize the initial threshold and the weight of the neuron so as to select the appropriate threshold and weight, and to improve the accuracy and stability of the constitutive model.

The damper is designed to reduce the impact of earthquake on structure. Its effect is mainly determined by three factors: the performance of the device, the installation location and the number of devices being arranged. Even if the damper has a good damping effect and a big actuating force, it is difficult to achieve the desired damping if the location or number of devices is inappropriate. Therefore, in order to improve the efficiency and cost effectiveness of SMA control system, the author optimizes the installation location and number of SMA wire by the optimization algorithm which is suitable for SMA control system. In this paper, the author firstly carries out mechanical property test of austenite SMA wire and establishes a genetic optimized BP network constitutive model in reference to the material property test. Based on the constitutive model, the author uses the improved genetic algorithm to optimize the configuration of SMA control system in a spatial model structure, and performs the simulation analysis of the dynamic response of the optimal configuration by MATLAB, aiming at verifying the feasibility of applying the genetic optimized BP network constitutive model and the improved genetic algorithm in the SMA control system.

2. Material characteristic test of SMA

The chemical composition of the SMA wire tested is Ti-51% atNi alloy with a diameter of 1.0mm. See Figure 1, Test equipment for Taiwan Hungta HT-2402 computer servo control materials testing machine. The test pieces are 300mm long and 100mm in terms of effective length. Before the load is applied each time, apply tensile stress to the test pieces. The loading rate is 10mm/min, 30mm/min, 60m/min and 90mm/min respectively. Both loading and unloading are carried out at a constant rate. In each cycle, the loading continues until the wire material reaches the strain amplitude, which is 3%, 6% and 8% respectively, and the unloading terminates when the axial force of the wire material falls below 5N. Carry out 30 cyclic loadings under each working condition. See Figure 2 for the stress-strain curve of the tensile test performed when the strain amplitude is 6% and the mechanical properties of the SMA are stable. It can be seen that the stress-strain curve of the SMA wire has obvious changes with the increase of loading rate but the mechanical properties of the SMA wire remain largely unchanged.

Fig.1 Austenitic Ni - Ti SMA

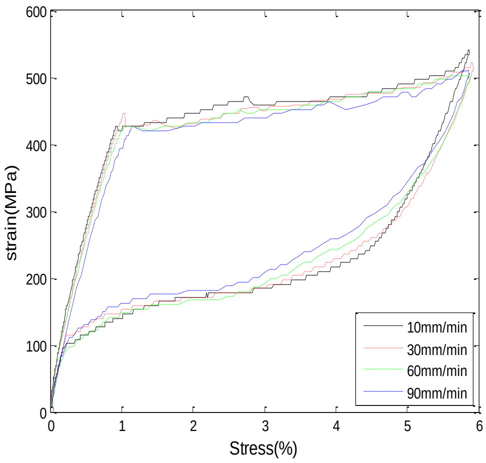


Fig.2 Stress-strain curve at different loading rate

3. GA optimized BP network constitutive model

3.1 BP network algorithm

The BP neural network is a feed-forward network trained with error back propagation method. It consists of multiple layers, including the input layer, hidden layer and output layer [18]. The weight/threshold of the neural network is assigned by the system randomly. As the initial weight/threshold is different for each round of training, the final weight/threshold and the model of the neural network varies from round to round. In particular, if only a limited amount of data is available, it is possible to generate two completely different neural network models in two rounds of training. On the contrary, sufficient and widely available training data narrows the difference between trained models but slows down the training convergence of the network.

The genetic algorithm adopts the probabilistic parallel global search, while the artificial neural network is capable of self-learning. To make full use of the advantages of the two methods, the two algorithms are integrated into a new algorithm featuring both the robustness and self-learning ability of the neural network and the global search ability of the genetic algorithm. The integration avoids the variation of the BP network trained with different initial weighs/thresholds, and prevents the fluctuation and non-convergence caused by improper initial weight/ threshold value. See Figure 3 for the initial weight/threshold of genetic optimized BP network.

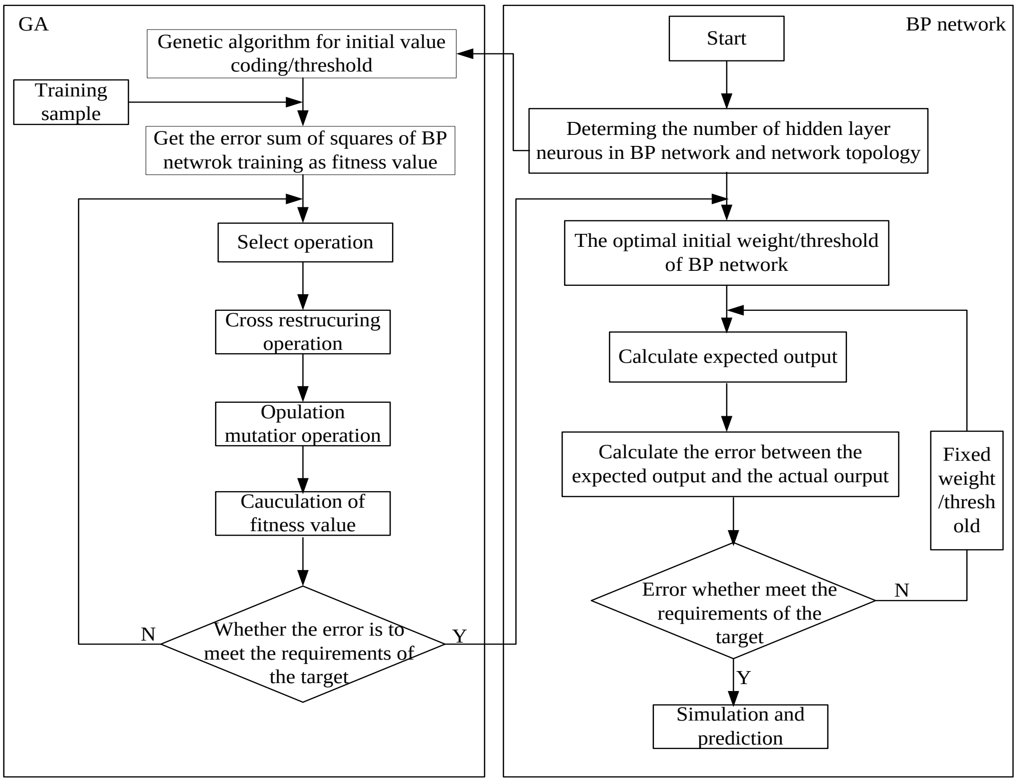


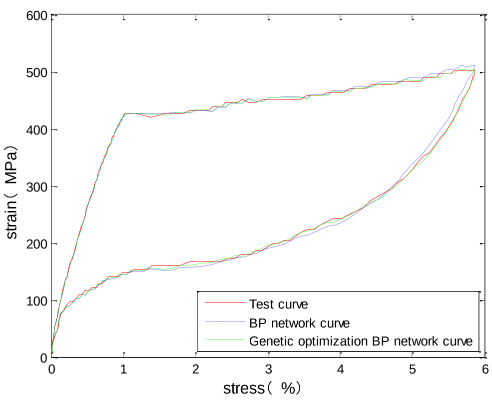
Fig.3 BP network flow chart of genetic algorithm optimization

3.2 Neural network constitutive model

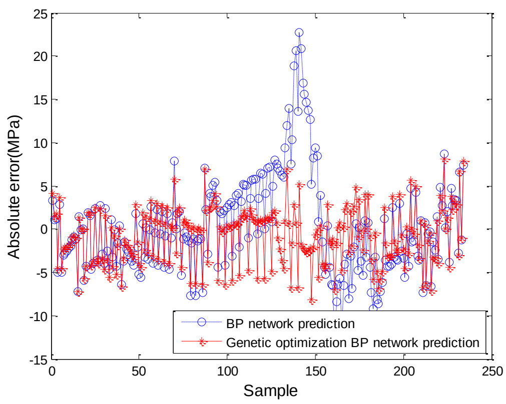
According to the BP theorem, Kolmogorov theorem and Robert Hechi Nielson, approximation with arbitrary accuracy can be achieved with a BP network with one hidden layer [19]. This paper uses a three-layer BP network to establish the constitutive model of SMA. On the input layer, there are 6 neurons, namely rate, strain at this moment, and stress and strain at the previous moment and at the moment before the previous moment. On the output layer, there is only one neuron, i.e. the stress at this moment. On the hidden layer, the number of neurons is set as 20 by estimation. The neuron activation function is logsig for the hidden layer and purelin for the output layer.

3.3 Simulation results contrast of two kinds of constitutive model

Using MATLAB, the author sets up the BP network constitutive model and the genetic optimized BP network model for austenite SMA. For the un-optimized BP network, the initial weight/threshold is assigned randomly by the system. For the optimized BP network, the initial weight/threshold is optimized by the genetic algorithm. The last cycle data of the material property test is taken as the training sample of BP network. The training function is trainlm, the maximum number of training is 1,000, the target error is 10^{-5}, and the learning rate is 0.1. The neural network constitutive model of SMA can be obtained by writing the code of simulation program with the toolbox of neural network and genetic algorithm in MATLAB. When the diameter is 1.0mm, the loading rate is 60mm/min, and the strain amplitude is 6%, the comparison and error of stabilized stress-strain curves of SMA wire, respectively generated by the two models, are displayed in Figure 4. As shown in the figure, the genetic optimized BP neural network constitutive model makes a better prediction of the mechanical behavior of SMA because its prediction curve is in better agreement with the experimental curve, its average absolute error is smaller and its model accuracy is higher. Thus, the genetic optimized BP neural network constitutive model is a highly accurate rate dependent constitutive model that can explicitly demonstrate the effect of loading rate on the super-elasticity of SMA.



(a)Stress-strain curve comparison



(b) prediction error curve

Fig.4 The comparison of two BP networks’ prediction errors

4. Improved GA

In traditional genetic algorithm, the location of SMA cable is often optimized through binary coding. If the genetic value of the locus of an individual equals 0, there is no SMA wire at the corresponding location of the structure; if the genetic value of the locus of an individual equals 1, there is a SMA wire at the corresponding location of the structure. After genetic crossover, the genetic value (0/1) of the new individual in traditional genetic algorithm would inevitably change, resulting in alterations to the number of SMA wires during the optimization process. In other words, the traditional genetic algorithm cannot solve the optimization issue when the number of SMA wire is fixed. Therefore, it is necessary to improve the traditional genetic algorithm so that it can optimize the configuration of SMA control system efficiently. This paper mainly improves the algorithm from three aspects: coding mode, crossover operator and mutation operator.

The coding method is modified as follows: floating-point coding is used, but the variables are integer-constrained. The length of an individual indicates the number of SMA wires to be arranged, and the genetic value of an individual locus is the position number of the SMA wire. As the genetic value reflects all possible placement positions, the genetic values of the same individual should be different from each other so that only one SMA wire is arranged at the same location in the structure. The crossover operator is improved as follows: carry out crossover with the traditional genetic crossover operator to generate a new individual, and find out the loci of the same genetic value in the new individual; keep the genetic value of one locus, and take the genetic values of other loci as random and unique integers. The mutation operator is modified as follows: When the mutation is defined, the genetic value of the mutated locus can only be taken as the allele which is not the same as other genes.

5. Optimal control of the structure under genetic optimized BP network constitutive model

5.1 Model structure

The model has a 2-span, 3-layer spatial structure. There are 2 spans along X-direction, both of which are 500mm in length, and 1-span along Z-direction. The entire structure is 600mm long. Vertically, the structure has three layers, each of which is 500mm in height. On each layer, a 12kg steel plate is placed as floor counterweight. There are 6 nodes on each layer. Each node is provided with a 1kg steel cube and a fixed spiral hole reserved for fixing SMA wire. All rod pieces are Q235 round pipes (wall thickness: 1mm; outside diameter: 10mm; elastic modulus: 206GPa; Poisson's ratio: 0.3; density: 7.85*10^{3}kg/m). The following assumptions are made to analyze the seismic response of the model structure: (1) All mass is concentrated at the nodes of each floor; (2) The initial operating temperature of each SMA wire is constant in its cross section and on the length direction. See Figure 5 for the nodes and rod pieces of the spatial model structure.

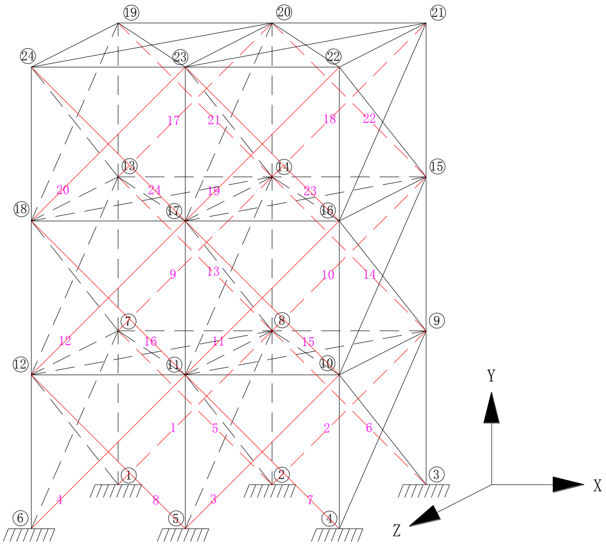


Fig.5 Space model structure

5.2 Optimization criteria and parameter setting

To study the vibration control effect of SMA wire on the spatial model structure, the sum of lateral interlayer displacements of the structure is taken as the objective function of optimization. The optimization criterion is:

$$J = \sum_i |\Delta_i| = \sum_i |s_i - s_{i-1}| \tag{1}$$

$$s_i = \frac{\sum_j s_{ij}}{\sum_j j} \tag{2}$$

Where, J is the value of the objective function; $|\Delta_i|$ is the interlayer displacement of the i-th layer; s_i is the absolute lateral displacement of the its layer, which equals the average lateral displacement of all nodes of the i-th layer; s_{ij} is the absolute lateral displacement of the j-th node of the i-th layer.

According to the basic principle of genetic algorithm, the fitness function can be designed as follows:

$$Fit = \frac{1}{J} = \frac{1}{\sum_{i} |s_i - s_{i-1}|} \tag{3}$$

As required, this function is single-valued, continuous, non-negative, and maximized. The larger the *Fit* value of the individual of the genetic algorithm, the smaller the objective function value, the greater the fitness of the individual, and the better the configuration of the corresponding SMA control system.

The operating parameters of the improved genetic algorithm are as follows: the initial population size is 40, the maximum number of generations is 50, and the crossover probability P_c=0.8. When the number of generations for which the optimal individual is invariant in the population does not exceed 5, the mutation probability P_m is 0.05. When the number of generations for which the optimal individual is invariant in the population surpasses 20, the mutation probability P_m is 0.2. When the number of generations for which the optimal individual is invariant in the population falls between 5 and 20, the mutation probability is linearly interpolated between P_m and GP_m.

5.3 Optimal control result and analysis

The EL-Centro earthquake wave is selected as the seismic excitation for the optimization of austenitic SMA control system and the simulation of structural vibration response. The excitation lasts 20s at an interval of 0.02s. The peak acceleration amplitude is 200gal. The loading is unidirectional along the X direction. To realize a larger deformation of the SMA cable and to consume more energy, SMA wires are arranged only at oblique locations in the X-Y plane, that is, there are 24 possible locations to place SMA cable in the optimized configuration. The MATLAB is used to write a program to analyze the vibration control of the system.

Table 1 lists the optimal placement location, objective function value, and corresponding damping effect of different number of SMAs in the spatial model structure. As shown in the table, the optimized SMA can suppress the seismic response of the spatial model structure. The improved genetic algorithm has a smaller objective function value and better vibration control effect. With the increase of the number of generations, both the optimal value and the mean value of the objective function decrease gradually, indicating that the optimal value and the mean value are in a gradually converging and the range ability of the objective function value keeps shrinking. The damping effect is not necessarily direct proportional to the number of SMA cables. When the number of SMA exceeds a certain number, the damping effect is reduced. Therefore, the only way to economically and effectively reduce the seismic effect is to reasonably configure the number and location of the SMA cables.

According to the optimization results, the damping effect is optimal when 4 SMA cables are arranged and configured by the genetic algorithm. In this case, the sum of interlayer displacements of the structure is 26.8mm, down by 44.51% from 48.3m in the uncontrolled condition. Figure 6-8 and Figure 9-11 show the curves of displacement and acceleration time-history curves for each layer of the model structure under the uncontrolled, random and optimized conditions when 4 SMA cables are arranged and controlled by MATLAB simulation. As shown in the figures, the genetic optimized SMA control system is more effective in reducing the seismic response of the structure than the uncontrolled or random arrangements. On the whole, the seismic response of the controlled structure is more than 15% lower than that of the uncontrolled structure, and the control effect of the interlayer displacement response of the structure is more obvious than that of the acceleration response. Moreover, the damping effects of the first and second layers are more obvious than that of the third layer. On the bottom two layers, the inter-story displacement can be reduced by more than 40%, and the acceleration response can be reduced by more than 20%.

Tab.1 SMA optimal layout location

Number of austenite SMA	Location optimization results	Objective function value (m)		Damping effect (%)
		Un-improve	Improve	
0(Uncontrolled)	---------------------------	0.0483	0.0483	-------------------
2	4,15	0.0352	0.0337	30.23
4	4,6,12,14	0.0285	0.0268	44.51
6	2,6,7,13,14,20	0.0254	0.0235	51.35
8	4,7,8,13,14,15,21,24	0.0231	0.0216	55.28
12	2,8,9,10,11,13 14,15,19,20,22,23	0.0228	0.0212	56.11
16	2,3,4,5,9,10,11,12,13	0.0239	0.0228	52.80

	14,15,16,17,19,21,24			
20	1,3,4,5,6,9,10,11,12,13,14 15,16,17,19,20,21,22,23,24	0.0269	0.0263	45.55
24	Suffusion	0.0271	0.0271	43.89

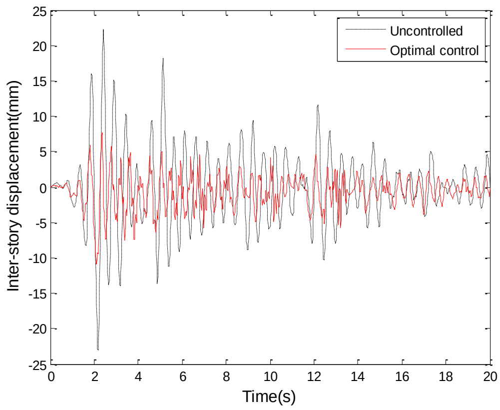


Fig.6 Displacement time history curve at first layer

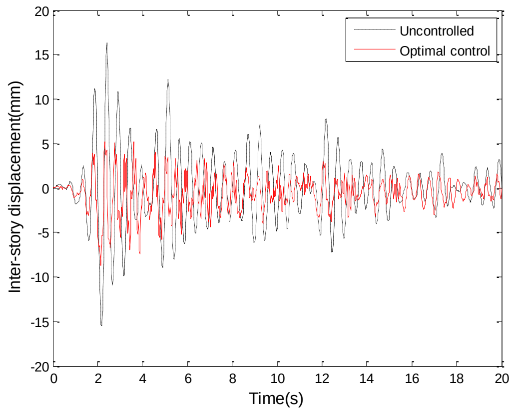


Fig.7 Displacement time history curve at second layer

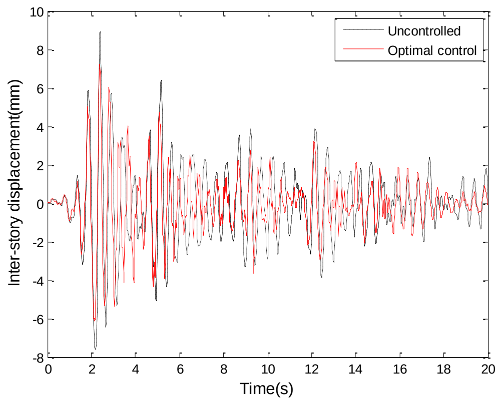


Fig.8 Displacement time history curve at third layer

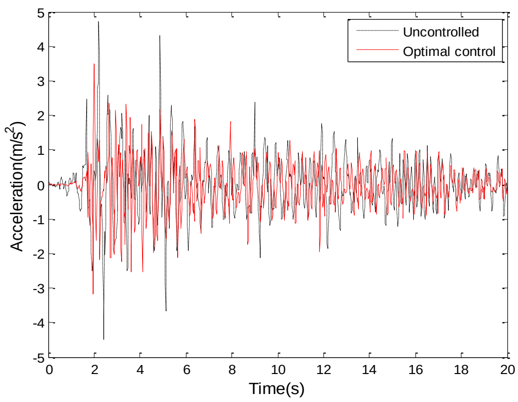


Fig.9 Acceleration-time history curve at first layer

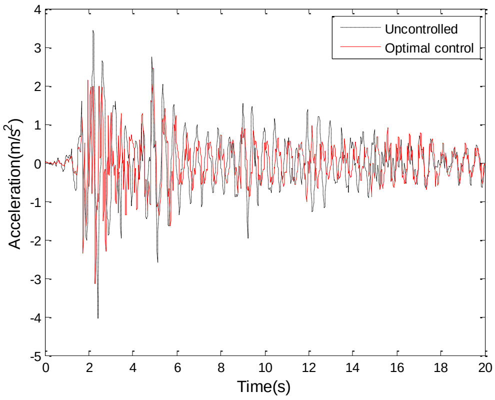


Fig.10 Acceleration-time history curve at second layer

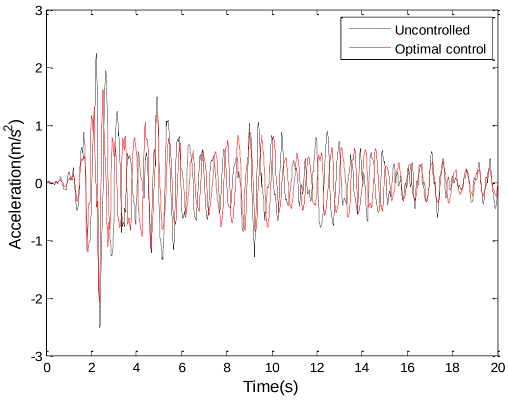


Fig.11 Acceleration-time history curve at first layer

Conclusions

On the basis of the SMA material property test, this paper establishes a genetic optimized BP network constitutive model for SMA by applying the intelligent algorithm. The prediction curve of the genetic optimized model has a better agreement with the experimental curve and smaller average absolute error than that of non-optimized BP network, indicating that the optimized model is a highly accurate rate dependent constitutive model that can explicitly demonstrate the effect of loading rate on the super-elasticity of SMA.

As it ensures the number of SMAs is always as desired in the process of optimization, which is the precondition for obtaining better locations of SMA cables, the improved genetic algorithm boasts higher global searching efficiency and better damping effect.

The structural vibration control analysis shows that: The damping effect is not necessarily direct proportional to the number of SMA cables. When the number of SMA exceeds a certain number, the damping effect is reduced. Therefore, the only way to economically and effectively reduce the seismic effect is to reasonably configure the number and location of the SMA cables.

The genetic optimized BP network constitutive model is taken as the constitutive model of SMA cable. Optimized by the genetic algorithm, the SMA control system can more effectively reduce the seismic response of the structure. The damping effect is optimal when 4 SMA cables are arranged. In this case, the sum of interlayer displacements is down by 44.51%. Besides, the seismic response of the controlled structure is more than 15% lower than that of the uncontrolled structure, and the control effect of the interlayer displacement response of the structure is more obvious than that of the acceleration response.

Acknowledgements

The research described in this paper was financially supported by the National Natural Science Foundation of China (No.51178388;51678480), Xi'an building university of science and technology innovation team funding plan, Scientific Research Plan Project of Shaanxi Education Department (14JK1420), Central University Special Foundation for Basic Scientific Research Business of Chang'an University in China (310812161009).

References

1. L. Janke, C. Czaderski, M. Motavalli, et al, Applications of shape memory alloys in civil engineering structures—Overview, limits and new ideas, 2008, Materials and Structures, vol. 5, no. 38, pp.578-592.
2. S. L.Wang, Application of shape memory alloy in the structure control, 2000, China, Xi 'an, Science and technology press.
3. N. Shajil, S. M. Srinivasan, M. Santhanam, An experimental study on self-centering and ductility of pseudo-elastic shape memory alloy (PESMA) fiber reinforced beam and beam-column joint specimens, 2016, Materials and Structures, vol. 3, no. 49, pp. 1-11.
4. A. Rao, A. R. Srinivasa, J. N. Reddy, Introduction to Shape Memory Alloys// Design of Shape Memory Alloy (SMA) Actuators, 2015, pp. 1-31.
5. S. Langbein, A. Czechowicz, Introduction to Shape Memory Alloy Actuators // Shape Memory Alloy Valves, 2015, Springer International Publishing, pp. 41-72.
6. D. J. Xing, Z. X. Li, The Study and Application of Shape Memory Alloy in Civil Engineering, 2006, Materials Review, vol. 8, no. 20, pp. 62-68.
7. W. Wang, The Constitutive Model and Experimental Study on Shape Memory Alloys, 2011, China, Dalian, Dalian university of technology.
8. O. Heintze, A computationally efficient free energy model for shape memory alloys – experiments and theory, 2004, PhD thesis, North Carolina State University.

9. 9. K. Otsuka, X. Ren, Physical metallurgy of Ti–Ni-based shape memory alloys, 2005, Progress in Materials Science, vol.5, no.50, pp.511-678.
10. B. C. Chang, J. A. Shaw, M. A. Iadicola, Thermodynamics of Shape Memory Alloy Wire: Modeling, Experiments, and Application, 2006, Continuum Mechanics and Thermodynamics, vol.1, no.18, pp.83-118.
11. Y. G. Zhu, Constitutive model of shape memory alloys, 2001, Chinese Journal of Materials Research, vol. 3, no. 15, pp. 263-268.
12. B. Zhou, Y. J. Liu, J. S. Leng, G. P. Zou, A macro-mechanical constitutive model of shape memory alloys, 2009, Science China Physics, Mechanics & Astronomy, vol. 9, no. 52, pp. 1382-1391.
13. P. Thamburaja, N. Nikabdullah, A macroscopic constitutive model for shape-memory alloys: Theory and finite-element simulations, 2009, Computer Methods in Applied Mechanics & Engineering, vol. 9-12, no. 198, pp. 1074-1086.
14. J. H. Chung, J. S. Heo, J. J. Lee, Implementation strategy for the dual transformation region in the brinson sma constitutive model, 2007, Smart Materials & Structures, vol. 1, no. 16, pp. 329-31.
15. L. C. Brinson, M. S. Huang, Simplifications and Comparisons of Shape Memory Alloy Constitutive Models, 1996, Journal of Intelligent Material Systems & Structures, vol. 1, no. 7, pp. 108-114.
16. Y. J. Peng, Neural network control method research of structural vibration control, 2006, China, Wuhan, Wuhan University of Technology.
17. M. Jha, B. Nisha, S. Rama, M.F. Qureshi, Artificial Intelligence Based Fault Diagnosis of Power Transformer-A Probabilistic Neural Network and Interval Type-2 Support Vector Machine Approach, 2014, International Journav of Heat and Technology, vol. 19, no. 1, pp. 71-89.
18. Y. Q. Lei, Y. F. Du, Smart active fault tolerant control algorithm based on neural network for structural vibration control, 2014, Journal of Vibration & Shock, vol. 13, no. 33, pp. 117-191.
19. M.Y. Xue, Application of neural network and genetic algorithms in structural damage identification, 2010, China, Dalian, Dalian university of technology.