Parameter Identification of GMA Nonlinear Dynamics Model Based on ICPSO

Chang Guanghui and Zhang Yachao
College of Power Engineering, Naval University of Engineering, Wuhan, China
Email: cgh_navy@163.com, Frank910424@163.com

***Abstract*—In order to improve the control precision of the giant magnetostrictive actuator (GMA), the unknown parameters of the hysteresis nonlinear model are quickly identified based on the test data before use, and the GMA nonlinear dynamic model is established based on the free energy hysteresis model. Aiming at the shortcomings of standard particle swarm optimization (PSO) algorithm and the tendency to fall into local optimum in the late iteration, an improved chaotic particle swarm optimization algorithm with dynamic adjustment of flight time and optimal position of the group through chaotic traversal optimization is proposed. ICPSO), and the algorithm is applied to the parameter identification of actuator nonlinear model. Experiments show that the algorithm can identify GMA nonlinear dynamic model parameters with high efficiency, and the identified model can be well fitted with experimental data. The hysteresis displacement error is within 3%, and the kinetic model is highly reproducible by multiple comparisons.**

***Index Terms*—GMA, parameter identification, chaotic**

I. Introduction

The Giant Magnetostrictive Actuator (GMA) has the advantages of simple structure, large strain, small volume, fast response and strong output force. It has a wide range of fields in fluid machinery control, precision positioning mechanism, active noise reduction and ultra-precision machining [1]. Application prospects. At present, the hysteresis models that can be used to describe GMA are: Preisach model, Jiles-Atherton model, free energy model and neural network model. Compared with other models, the free energy hysteresis model has the advantages of simple model structure, physical properties of parameters and easy modification of external influences (such as eddy current loss, temperature, etc.), but it is often used for parameter identification in the free energy hysteresis model. In some optimization algorithms, Particle Swarm Optimization (PSO) is widely used. However, PSO algorithm has the disadvantages of being easy to fall into local optimum and slow convergence in the later stage, especially for nonlinear hysteresis models such as GMA [2]. It is difficult to get a satisfactory global optimal solution. Therefore, this paper improves PSO and combines chaos optimization method to propose an improved chaotic particle swarm optimization algorithm (ICPSO), which is applied to the parameter identification of GMA nonlinear dynamic model. Simulation and experimental research show that the improved algorithm is feasible and effective.

II. GMA Nonlinear Model

A. *The Working Principle of GMA*

A schematic diagram of the structure of the GMA is shown in Fig. 1. GMA works as follows: the output rod, the outer casing and the bottom cover are made of magnetically permeable materials. They can form a closed magnetic circuit with the giant magnetostrictive rod. The magnetic field generated by the coil acts as the driving magnetic field, and the driving magnetic field is input [3], [4]. The change of current changes, and under the action of the changing driving magnetic field, the giant magnetostrictive rod undergoes expansion and contraction due to the axial magnetostrictive effect, thereby converting electromagnetic energy into mechanical energy.

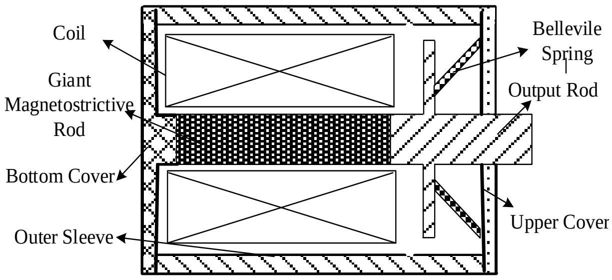


Figure 1. GMA structure Sketch diagram.

B. *GMA Nonlinear Dynamic Model Based on Free Energy Hysteresis*

The magnetization expression of the free energy hysteresis model：

$$\left[M(H)\right](t)=\alpha\int_0^{\infty}\int_{-\infty}^{\infty}\bar{M}\left(H+H_I;H_C,\xi\right)(t)e^{-H_I^2/2b^2}e^{-\left[\ln\left(H_C/\bar{H}_C\right)/2c\right]^2}dH_I dH_C \quad (1)$$

In the equation：

$$\left[\bar{M}(H;H_C,\xi)\right](t)=\begin{cases}\left[\bar{M}(H;H_C,\xi)\right](0) & ,\tau(t)=\phi\\ \dfrac{H}{\eta}-M_R, & \tau(t)\neq\phi\, and\left(\max\tau(t)\right)=-H_C\\ \dfrac{H}{\eta}+M_R, & \tau(t)\neq\phi\, and\left(\max\tau(t)\right)=H_C\end{cases} \quad (2)$$

Manuscript received November 27, 2019; revised July 19, 2020.

doi: 10.18178/ijmerr.9.9.1300-1305

The time set $\tau(t)$ at which the average localized magnetization $\bar{M}$ is converted is expressed as：

$$\tau(t) = \{t \in 0, T_f | H(t) = -H_c \quad \text{or} \quad H(t) = H_c\} \tag{3}$$

In the equation, α is the probability distribution parameter of free energy, M_R is the magnetization intensity when the free energy obtains the minimum value, η is the slope of the hysteresis core, $\bar{H}_c$ is the average coercive force, the b interaction field density probability distribution parameter, c is the core field density Probability distribution parameters.

Under certain pre-stressing stress, the relationship between magnetostriction λ and magnetization M is approximately the following quadratic domain-transformation model.

$$\lambda = \frac{3}{2}\lambda_S\left(\frac{M}{M_S}\right)^2 \tag{4}$$

where λ_S is saturation magnetostriction and M_S is saturation magnetization.

Considering the interference force G and pre-compression stress σ that GMA is subjected to during operation, the transfer function of GMA output displacement and input current based on nonlinear piezomagnetic equation and dynamics principle is:

$$y = \frac{1}{Ms^2+Cs+K}(A_r E^H \lambda + MG - \sigma A_r) \tag{5}$$

In the equation $M = M_r + M_l$, $C = C_r + C_l$, $K = K_r + K_l$, $M_r = \frac{\rho l_r A_r}{3}$, $C_r = \frac{C_D A_r}{l_r}$, $K_r = \frac{E^H A_r}{l_r}$, Here M_r , C_r , K_r , M_l , C_l , K_l are the equivalent mass, equivalent damping coefficient and equivalent stiffness coefficient of the giant magnetostrictive rod and the load, respectively, l_r , A_r , ρ , C_D , E^H are respectively supermagnetic Length, cross-sectional area, mass density, internal damping coefficient, Young's modulus of the telescopic rod. Equations (1), (4), and (5) constitute a nonlinear dynamic model of GMA.

III. Improvement of Particle Swarm Optimization

A. Particle Swarm Optimization

The basic idea of the PSO algorithm is to find the optimal solution through the cooperation and information sharing among individuals in the population. Suppose a particle swarm contains n particles and extends into the N dimension space. The position of the particle i in the N dimension space is represented as vecto $X_i = [x_{i1}, x_{i2}, \cdots, x_{iN}]$, the flight speed is expressed as vector $V_i = [v_{i1}, v_{i2}, \cdots, v_{iN}]$, and the individual optimal value of the i particles is recorded as $pbest_i$. The global optimal value of the entire population is recorded as $gbest$, and the particle updates its speed and position by the following equation.

$$V_i(t+1) = wV_i(t) + c_1 r_1[pbest_i(t) - X_i(t)] + c_2 r_2[gbest(t) - X_i(t)] \tag{6}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{7}$$

In the above equation: w is the inertia weight; c_1, c_2 are the acceleration constants, and r_1 and r_2 are random numbers independent of $(0,1)$.

B. Improved Chaotic Particle Swarm Optimization Algorithm

It has been shown that there is a coupling effect between the length and direction of $wV_i(t)$ and $pbest_i(t)$ and $gbest(t)$, resulting in slow update. In addition, in the PSO algorithm, when the particle is updated in position, the particle is fixed every time of flight, and sometimes the particle oscillates back and forth around the optimal solution. Because at the beginning of the iteration, the particles are far from the optimal position, the flight time of the particles is longer, which is conducive to faster flight to the optimal position; but in the later stage of the iteration, the particles are closer to the optimal position due to the larger flight time [5]-[8]. And "flying through" the optimal position, resulting in a decline in particle search performance. Therefore, in order to improve the performance of the PSO algorithm, the speed and position update equation is improved. The basic idea is: firstly, the (6) is decomposed into three-step updates, and three speeds $V_1(t+1)$, $V_2(t+1)$, $V_3(t+1)$ are obtained, when the particle update speed exceeds the maximum. When the speed is v_{max}, the maximum speed value is taken to prevent the influence of the speed on the search accuracy. The specific equations are as follows:

$$V_1(t+1) = wV_i(t) \tag{8}$$

$$V_2(t+1) = V_1(t+1) + c_1 r_1[pbest_i(t) - X_i(t)] \tag{9}$$

$$V_3(t+1) = V_2(t+1) + c_2 r_2[gbest(t) - X_i(t)] \tag{10}$$

Then, in (7), the velocity term is multiplied by the dynamically adjusted flight time, and the three speeds generated by the decomposition are respectively brought into the corresponding three update positions $X_1(t+1)$, $X_2(t+1)$, $X_3(t+1)$. The improved location update equations are as follows:

$$X_1(t+1) = X_i(t) + TV_1(t+1) \tag{11}$$

$$X_2(t+1) = X_i(t) + TV_2(t+1) \tag{12}$$

$$X_3(t+1) = X_i(t) + TV_3(t+1) \tag{13}$$

$$T = T_0\left(1 - \frac{kt}{t_{max}}()\right) \tag{14}$$

Among them, T is the dynamic flight time, T_0 is the maximum flight time, k is the proportional coefficient, t is the current number of iterations, and t_{max} is the maximum number of iterations. Finally, the fitness function of the three positions is evaluated by the objective function $f(x)$, and the best position is selected as the final result.

The particle position update process of the improved PSO algorithm is shown in Fig. 2.

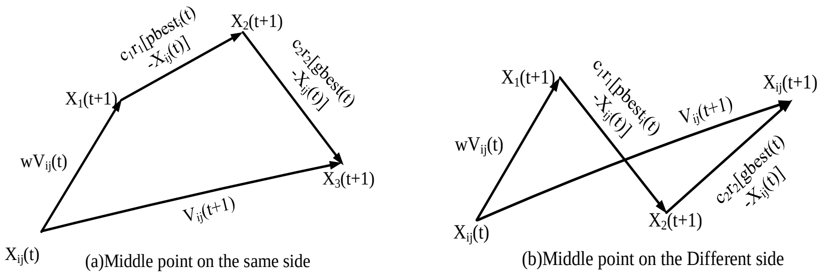


Figure 2. Location update process vector.

For the optimal position of the group, it is realized by chaotic traversal optimization. Logistic image is selected to generate chaotic variables. The iterative equation is as follows:

$$\mathrm{Z_{n+1}} = \mu \mathrm{Z_n}(1 - \mathrm{Z_n}) \quad \mathrm{n} = 0,1,2\cdots \tag{15}$$

The method of changing the chaotic variable back to the optimization variable adopts linear mapping, and its expression is as follows:

$$\mathrm{z_n} = \mathrm{a} + (\mathrm{b} - \mathrm{a})\mathrm{x_n} \tag{16}$$

In the above equation, for the improved PSO algorithm, a and b are expressed as the minimum and maximum values of the particle positions. In the iterative optimization process, when the chaotic variables are traversed in the$[0,1]$interval, the corresponding optimal position of the group is traversed within the corresponding range of values to find the optimal position.

In summary, the basic idea of the improved chaotic particle swarm optimization algorithm (ICPSO) is: firstly improve the speed and position update equation of PSO, and decompose (6) into three-step update, find the fitness value and find The optimal position of the individual and the optimal position of the group, then transform the required optimization variables (the optimal position of the group) into chaotic variables, and transform the range of the optimization variables into the traversal range of the chaotic motion for chaos optimization, and then optimize the The chaotic variable is expressed as an optimization variable [9]. By continuously updating the velocity and position of the particle, the optimal solution of the variable is finally obtained. The calculation steps are described as follows:

Step 1 Randomly generate$n$particle populations, set relevant parameters of ICPSO algorithm: particle swarm, chaos algorithm maximum iteration number M_1 , M_2 , inertia weight$w$, learning factorc_1,c_2, fitness error$e$, speed value range$[vmax_{min}]$and the position of the value range is$[xmax_{min}]$.

Step 2 Calculate the fitness value of each particle. The current position of the particle is recorded as$pbest_i$, and the optimal position of the fitness value in the entire group is recorded as$gbest$.

Step 3 Update the velocity and position of the particles according to the ICPSO algorithm update (8)~(14).

Step 4 Perform chaos optimization on the optimal position$gbest$of the population:

Map the optimization variable $gbest$ to the domain$[0,1]$of the Logistic equation:

$$\mathrm{Z_1^k} = \frac{\mathrm{gbest_k - x_{min,k}}}{\mathrm{x_{max,k} - x_{min,k}}} \tag{17}$$

The M_2 iteration is performed by the Logistic equation (15) to Z_1^k to obtain the chaotic sequence$Z^k = \left(Z_1^k, Z_2^k \cdots Z_{M_2}^k\right)$.

Linearly map chaotic sequences back to the original solution space:

$$\mathrm{gbest_{k,m}^*} = \mathrm{x_{min,k}} + \left(\mathrm{x_{max,k}} - \mathrm{x_{min,k}}\right)\mathrm{Z_m^k},\ \mathrm{m} = 0,1,2\cdots \mathrm{M_2} \tag{18}$$

Get a feasible solution sequence for chaotic variables: $gbest_k^* = \left(gbest_{k,1}^*, gbest_{k,2}^*, \cdots gbest_{k,M_2}^*\right)$.

Calculate the fitness value of each feasible solution vector in the feasible solution sequence, select the optimal fitness value and record its corresponding feasible solution vector as$Gbest_k^*$.

Step 6 Replace the position of any one of the particles in the current population with$Gbest_k^*$.

Step 7 If the requirement of the fitness error e is satisfied or the maximum number of iterations M_1 is reached, the search stops, and output$gbest$, otherwise skip to step 3.

IV. Model Parameter Identification Based on ICPSO

A. Identification Principle

In the GMA magnetostrictive nonlinear model, there are 13 parameters in total, they are λ_S,M_S,n,A_r,M_Z,C,K,M_R,η,$\bar{H}_c$,b,c_2,α. For a well-designed GMAn,A_r,M_Z,C are linear parameters either known or can be estimated, the magnetic nonlinearity of GMA is independent of them, mainly affected by nonlinear parameters such asλ_S,M_S,M_R,η,$\bar{H}_c$,b,c_2,α. In order to get the optimal parameters of GMA, the ICPSO algorithm is used to jointly optimize the eight parametersλ_S,M_S,M_R,η,$\bar{H}_c$,b,c_2,α. Set the parameter sss to be identified as:

$$\theta = [\lambda_S \quad M_S \quad M_R \quad \eta \quad \bar{H}_C \quad b \quad c \quad \alpha]^T \tag{19}$$

The objective function$f(x)$takes the squared sum of the error$e$of the actuator system output displacement$\bar{y}$of the Q sampling number and the mathematical model output displacement$y$, which is

$$f(\theta) = \sum_{k=1}^{Q} e^2(\theta, k) = \sum_{k=1}^{Q} \left(\bar{y}_0(k) - y_0(\theta, k)\right)^2 \quad (20)$$

B. *Identification Result*

The research team of the author of this paper designed and produced the GMA prototype, and tested it with the GMA performance test platform based on LabView. The experimental device is shown in Fig. 3. The relationship between input current and output displacement at different input frequencies is shown in Fig. 4.

Figure 3. GMA test experimental device.

The specifications of the selected giant magnetostrictive rod are $\Phi 10 \times 90$, Therefore $n = 14400/m$, $A_r = 7.85 \times 10^{-5} m^2$; Estimated from the characteristic parameters of the giant magnetostrictive rod and spring material $M_Z = 0.5Kg$, $C = 4.325 \times 10^3 \frac{Ns}{m}$, $K = 3.375 \times 10^7 \frac{N}{m}$. Parameter Identification of Current and Displacement Characteristics of Frequency at 50Hz in Fig. 4 Using ICPSO Algorithm, Identification results are as follows: Fig. 5 shows the identification process of the 8 parameters with the number of iterations. Fig. 6 shows the minimum value of the objective function as a function of the number of iterations. The minimum value of the objective function is 22.74. The comparison of the current and displacement characteristic curves calculated by the identified parameter values with the experimentally measured characteristic curves is shown in Fig. 7.

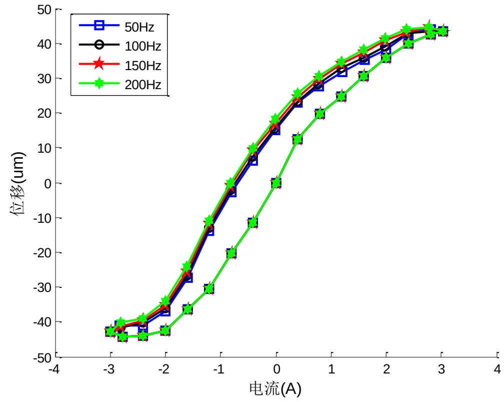
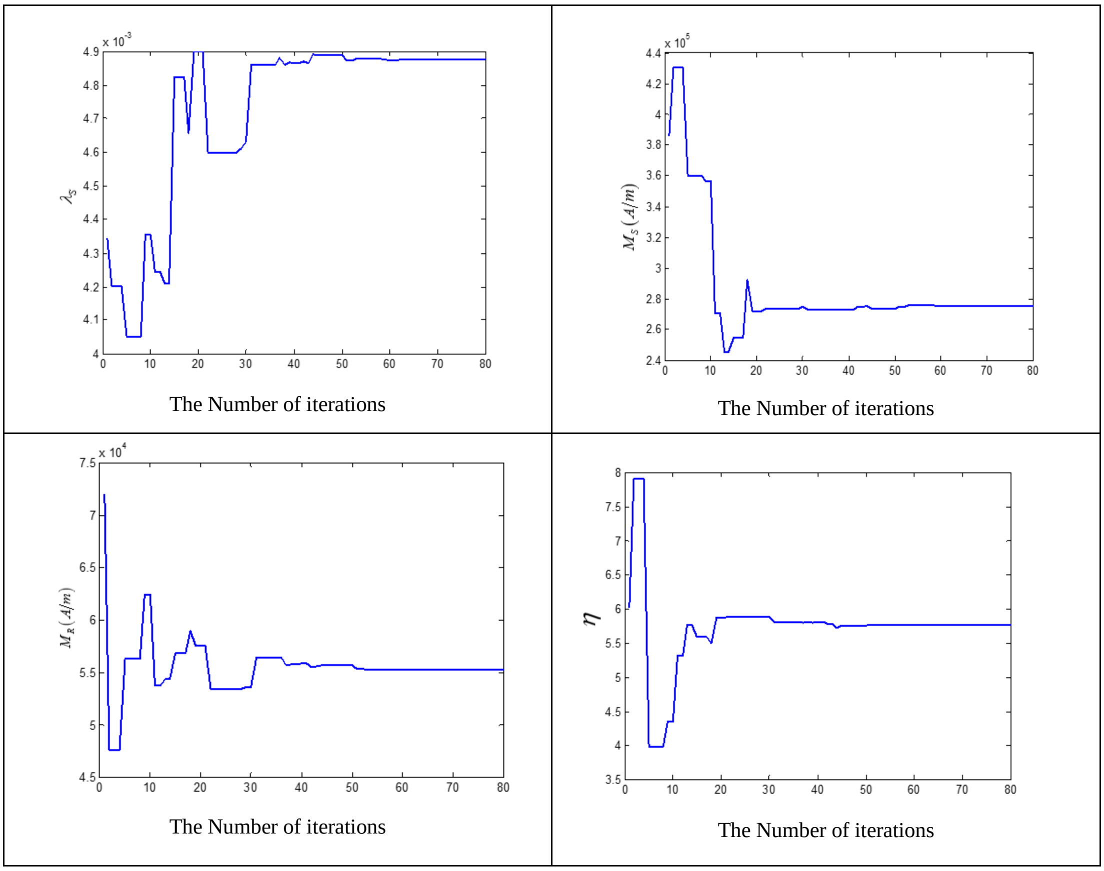


Figure 4. Relationship between input current and output displacement at different input frequencies.



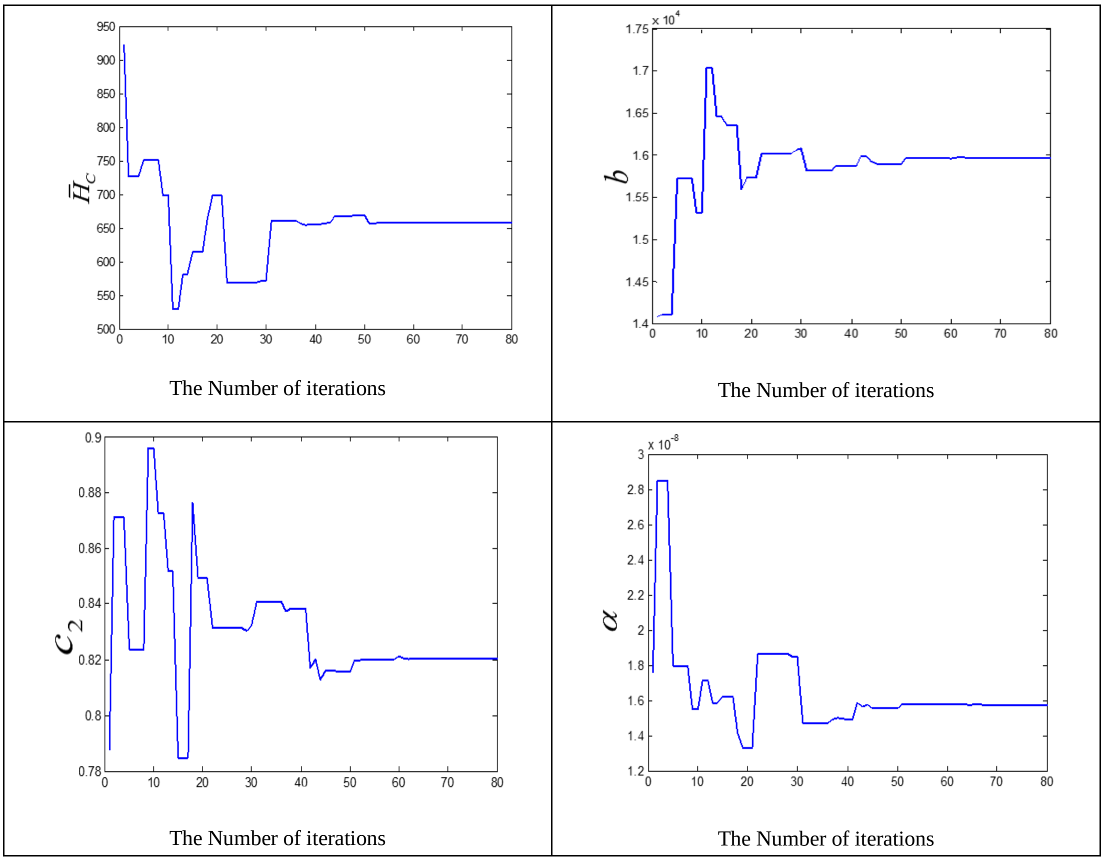


Figure 5. Parameter identification process with iteration number.

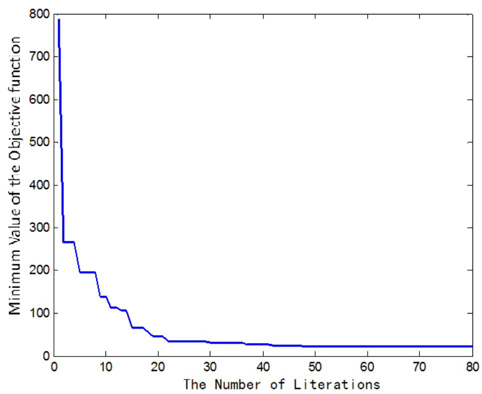


Figure 6. Objective function minimum iterative process.

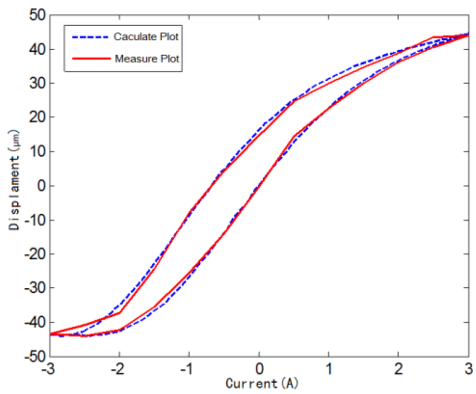


Figure 7. Comparison of experimental and calculated input current and output displacement μ .

V. Conclusion

Aiming at the shortcomings of PSO algorithm, the PSO is improved, and the chaos optimization is introduced to obtain the ICPSO algorithm, which is applied to the parameter identification of GMA nonlinear model. Through the simulation experiment, the satisfactory parameter values can be obtained, and the nonlinear parameters of the model can be effectively identified, which indicates that the algorithm is feasible for the parameter identification of nonlinear systems. It can be seen from Fig. 7 that the curve of the identification calculation agrees well with the experimentally measured curve, the similarity is high, and the hysteresis displacement error is within 3%, and the kinetic model is found to have high repeatability through multiple comparisons. It shows that the identification value obtained by applying ICPSO algorithm has high precision.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Chang Guanghui conducted the research; Zhang Yachao analyzed the data; all authors had approved the final version.

ACKNOWLEDGMENT

I would like to thank my instructor, Prof. Lou, who has given me numerous instructions about this paper.

REFERENCES

[1] Y. Wei-jian, Z. Yun, S. Kunnath, et al. "Identification of localized frame parameters using higher natural modes," *Engineering Stuuctures*, vol. 30, no. 11, pp. 3082-3094, 2008.

[2] S. A. Neild, M. S. Williams, P. D. Mcfadden, "Nonlinear vibration characteristics of damaged concrete beams," *Journal of Structural Engineering*, vol. 129, no. 2, pp. 260-268, 2003.

[3] H. Melhem, H. Kim, "Damage detection in concrete by fourier and wavelet analyses," *Journal of Engineering Mechanics*, vol. 129, no. 8, pp. 571-577, 2003.

[4] S. Z. Maas, A. Rbes, D. Waldmann, et al. "Damage assessment of concrete structures through dynamic testing methods," *Engineering Structures*, vol. 34, no. 1, pp. 351-62, 2012.

[5] M. Ruzzene, A. Fasana, L. Garibalei, et al. "Natural frequencies and dampings identification using wavelet transform:application to real data," *Mechanical Systems and Signal Processing*, vol. 11, no. 2, pp. 207-218, 1997.

[6] A. Kareem, K. Gurley, "Damping in structures: its evaluationand treatment of uncertainty," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 59, no. (2-3), pp. 131-57, 1996.

[7] J. Slavic, I. Simonovski, M. Boltezar, "Damping identification with the Morlet-wave," *Mechanical Systems and Signal Processing*, vol. 26, no. 5, pp. 1632-1645, 2011.

[8] Zhang Jia-jun, "Optimization parameters of PID controller parameters based on particle swarm optimization," *Computer Simulation*, vol. 27, no. 10, pp. 191-222, 2010.

[9] S. Liang, C. Ding-fang, L. Quan-guo, et al. "Modeling of time-delay in giant magnetostrictive actuator and smith strategy," *Journal of System Simulation*, vol. 21, no. 10, pp. 3017-3021, 2009.

Chang Guanghui was born in Hengshui, Hebei Province, China, in 1979. He is hold with the Ph.D. He is now working in NUE as an associate professor. He is mainly engaged in computer control and simulation, engine room automation.

Zhang Yachao was born in Shijiazhuang, Hebei Province, in 1990. He has received his master's degree and now is working in NUE as teaching assistant. His main research direction is computer control and simulation.