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Dynamic Modeling of a Giant Magnetostrictive Actuator Based on PSO

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ABSTRACT
In order to predict the output displacement of Giant Magnetostrictive Actuator (GMA), a dynamic model is established based on J-A model; the algorithm of modified Particle Swarm Optimization (PSO) is employed to identify the parameters of the proposed model. The calculated outputs using the identified model is compared with the test curves, with high agreement, the effectiveness of the proposed model and identification method is validated.

Key words: Magnetostrictive actuator, PSO, identification, hysteresis

INTRODUCTION

Giant Magnetostrictive Material (GMM) is a smart material with the properties of generating strains when excited by applied magnetic field. There are many advantages of GMM compared with other smart materials: Large elongation ($\geq$1000 ppm), fast response ($\leq$1 msec) and nanometer solution, actuators made of GMM (GMA), enjoys a prospect of applying in extensive fields stretches from active isolation of precise mechanics (Braghin *et al*., 2011, 2012), sonar transducer in high power and precise fluid control in wide bandwidth (Karunanidhi and Singaperumal, 2010).

However, like piezoelectric and shape memory actuators, GMA also suffer dominant hysteresis nonlinearity. Therefore, a thoroughly depict of hysteresis property of GMM considers the controllability and output precision of GMA. Hysteresis model of GMA is classified into Preisach type models and physical models, the former is approached based on a series of hysteresis curve tests under fix exciting conditions, thus, usually fail to describe the rate-dependent property of GMA while the physical models, such as Jiles-Atherton (J-A) model in dynamic condition employs the frequency factor into the dynamic expression, could describe the rate-dependent properties of GMA much better.

Researches show that parameters of J-A model are very difficult to be determined, as they are strongly interrelated nonlinear parameters. In recent studies, many intelligent optimization algorithms such as Simulated Annealing (SA) (Hamimid *et al*., 2012), Genetic Algorithm (GA) (Chwastek and Szczyglowski, 2006; Zheng *et al*., 2007) and differential evolution (DA) (Toman *et al*., 2008) are introduced to identify the J-A model.

In this study, a rate-dependent dynamic model is established based on J-A model, its parameters are identified based on modified PSO method, the calculated output displacement matches well with the test curves, proving the effectiveness of the proposed method.

MATERIALS AND METHODS

Dynamic model of GMA: The photo of GMA and its displacement sensor is shown in Fig. 1.

In dynamic condition (above 30 Hz), the J-A model have to be modified as a dynamic form as the eddy current loss and anomalous loss is counted (Jiles, 1994; Xu *et al*., 2013):

$$
\begin{aligned}
&H_e = H + \tilde{\alpha} M \\
&\tilde{\alpha} = \alpha + \frac{9}{2}\frac{\lambda_s \sigma_0}{\mu_0 M_s^2} \\
&M = M_{rev} + M_{irr} \\
&M_{rev} = c(M_{an} - M_{irr}) \\
&M_{an} = M + k\delta\frac{dM}{dH_e} - k\delta c\frac{dM_{an}}{dH_e} + \\
&\frac{\mu_0 d^2}{2\rho\beta}\left(\frac{dM}{dt}\right)\frac{dM}{dH_e} + \mu_0^{\frac{1}{2}}\left(\frac{GSV_0}{\rho}\right)^{\frac{1}{2}}\left(\frac{dM}{dt}\right)^{\frac{1}{2}}\frac{dM}{dH} \\
&M_{irr} = M_{an} - k\delta\left(\frac{dM_{irr}}{dH_e}\right)
\end{aligned}
\tag{1}
$$

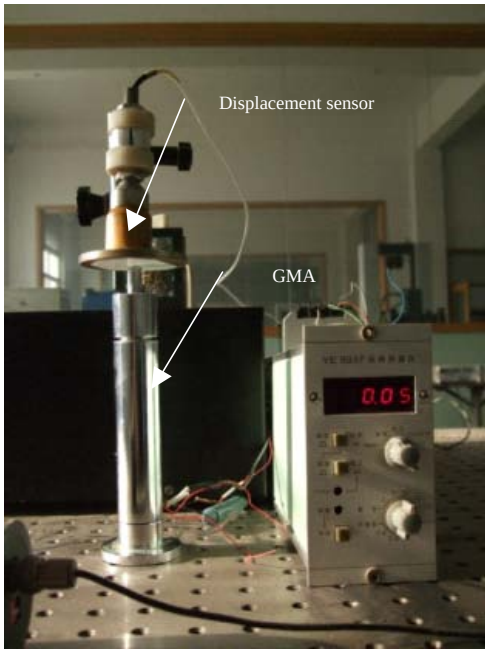

Fig. 1: GMA and displacement sensor

where, M_s and λ_s denotes the saturation magnetization and strain, respectively; H denotes the exciting magnetic field, H_e denotes the equivalent field internal the GMM bar; M_{irr} denotes the irreversible magnetization; M_{rev} denotes the reversible magnetization, a is named shape parameter, α is the mean-field parameter, k denotes the domain wall pinning parameter, c denotes the domain wall flexing parameter. $\delta = 1$ while $\dot{H} > 0$; $\delta = -1$ while $\dot{H} < 0$.

And the above equations could also be unified as a differential equation:

$$\left(\frac{\mu_0 d^2}{2\rho\beta}\frac{dH}{dt}\right)\left(\frac{dM}{dH}\right)^2 + \left(\frac{\mu_0 G S V_0}{2\rho\beta}\right)\left(\frac{dH}{dt}\right)^{\frac{1}{2}}\left(\frac{dM}{dH}\right)^{\frac{3}{2}} + \left[k\delta - \alpha\left(M_{an} - M + k\delta c\frac{dM_{an}}{dH_e}\right)\right]\left(\frac{dM}{dH}\right) - \left(M_{an} - M + k\delta c\frac{dM_{an}}{dH_e}\right) = 0 \quad (2)$$

where, dM/dH could be calculated through Newton-Raphson method. The M(H) curves could be integrated by the above differential equations using a 4th order adaptive-step Runge-Kutta method.

The magnetostriction property could be described with a famous quadratic model (Calkins *et al*., 2000):

$$\lambda = \frac{3}{2}\frac{\lambda_s}{M_s^2}M^2 \quad (3)$$

The element of generating displacement y could be regarded as a second-order system and described as a transfer function (Zheng *et al*., 2007):

$$y = \frac{AE^H\lambda}{M_{GMA}s^2 + C_{GMA}s + K_{GMA}} \quad (4)$$

where, M_{GMM}, C_{GMM}, K_{GMM} denotes the equivalent mass, damping and stiffness of GMM bar, respectively. The E^H denotes the Young's module of GMM.

In dynamic condition, the GMA system should be regarded as a vibration system, the equivalent mass should not be regarded as its actual mass; meanwhile, the damping parameter C and stiffness K is not so easy to test, these parameters are also to be determined.

At last, there are 10 parameters to be determined in the GMA model which forms a vector $\theta = [M_s\ \lambda_s\ a\ k\ \tilde{\alpha}\ c\ E^H\ M_{GMA}\ C_{GMA}\ K_{GMA}]^T$.

Identification based on PSO: In order to establish an effective parameter model of GMA, the vector θ should be recognized precisely, the idea of parameter identification is employed in this study.

The PSO method has been proposed by Eberhart and Kennedy (1995) which is derived from the research on birds feeding behavior. With a fine global convergence and easiness to realize, PSO method has been applied extensively in structure optimization and parameter identification.

In PSO, the potential solutions are represented as a particle swarm, there are two vectors attached in every particle, namely, velocity $V_i = [v_i^1, v_i^2 \ldots v_i^D]$ and position vector $X_i = [x_i^1, x_i^1 \ldots x_i^D]$, D denotes the dimensions of a solution space. Thus, D=10 in this case. The particles are firstly initialized randomly and 'fly' to search the global optimization under the following rule:

$$\begin{cases} v_i^{d+1} = wv_i^d + c_1r_1(p_i^d - X_i^d) + c_2r_2(BestS_i^{d+1} - X_i^d) \\ X_i^{kg+1} = X_i^d + v_i^{d+1} \end{cases} \quad (5)$$

where, v_i^d, x_i^d denotes the v and x vector in Step d; r_1 and r_2 denotes the random number within [0,1]; c_1 and c_2 denotes the acceleration coefficients. Then the fitness value in position X_i is calculated as:

$$J(X_i) = N/[\eta + \sum_{k=1}^{N} e^2(k)] \quad (6)$$

where, e(k) denotes the error between responses predicted by identified model and tested by the sensor; η is a constant avoiding zero occurs in denominator; the size of population is 80, the largest iteration step is 500.

The fitness value in current state $J(X_i)$ is compared with the particle best value p_i, if $J(X_i)$ is above p_i, p_i is refreshed as $J(X_i)$.

Then, $J(X_i)$ is compared with the global best value $BestS_i$, if $J(X_i)$ is above $BestS_i$, $BestS_i$ is refreshed as $J(X_i)$.

Parameter identification process based on PSO could be explained by Fig. 2.

Some modifications have been exerted in order to increase the speed and efficiency of optimization.

- A time-varying inertia weight has been introduced. According to literature (Alfi, 2011), a larger inertia weight improves the global performance while a smaller one helps to increase the local search precision. Thus a time-varying weight is in need to guarantee a quick lock of the global optimum region at start and a precise search within the region. The expression of the time-varying weight is exhibited:

$$w(i) = w_{max} - \frac{w_{max} - w_{min}}{G} i \quad (7)$$

- An adaptive mutation stage is employed. In previous evolution algorithms, like genetic algorithm, the mutation stage helps to increase the diversity of population and avoid 'prematurity'. The employment of adaptive mutation also benefits the global search of PSO (Tsoulos and Stavrakoudis, 2010). The mutation method in this study is expressed as:

$$K = \text{ceil}\,[\text{length}(\theta)\times \text{rand}_1]\ X_k = (X_{max\,k} - X_{min\,k})\times \text{rand}_2 \quad (8)$$

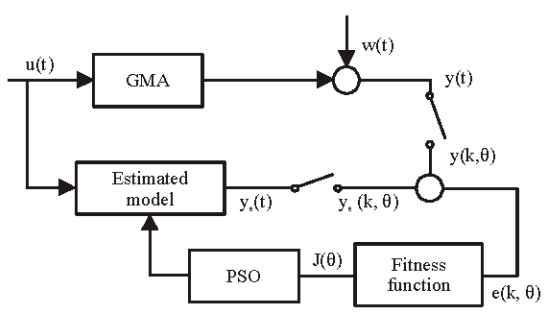

Fig. 2: Identification process of GMA

where, $rand_1$ and $rand_2$ is random within the range of [-1,1]; ceil() denotes the upper integer of a float; length() denotes the length of vector; X_{maxk} and X_{mink} denotes the upper and lower limit of the very parameter.

RESULTS

The setup of the GMA test system is shown as Fig. 3. In the test system, Picoscope2203 acts as signal generator and A/D acquisition; the reference voltage produced by Picoscope2203 is amplified by the power amplifier to drive GMA; the displacement sensor acquired the position signal and send it back to Picoscope2203.

The optimization range of GMA parameters are set in Table 1.

With the help of the proposed system, the calculated displacement curves could be compared with the tested curves, the comparing result is exhibited as Fig. 4.

Learned from Fig. 4, the displacement output predicts by the identified model of GMA coincides the test curves very well along the frequencies from 30-200 Hz.

Along with the increasing of driving frequency, the shape of hysteresis grows wider. This is due to the eddy current and abnormal loss is proportional with f and $f^{0.5}$, respectively.

DISCUSSION

This study concerns the dynamic modeling of a giant magnetostrictive actuator and its parameter identification method based on PSO. Some of the prior studies concerning

Table 1: Optimization range of GMA parameters

Parameter	Range
M_s (kA m^{-1})	740-800
λ_s (ppm)	1000-2000
a (A m^{-1})	3506-10518
c	0-0.3
$\tilde{\alpha}$	-0.1-0
k (A m^{-1})	1642-4925
E^H (MPa)	30-40
M (kg)	0.08-0.12
C (Nsec m^{-1})	10650-15950
K (kN m^{-1})	2000-3000

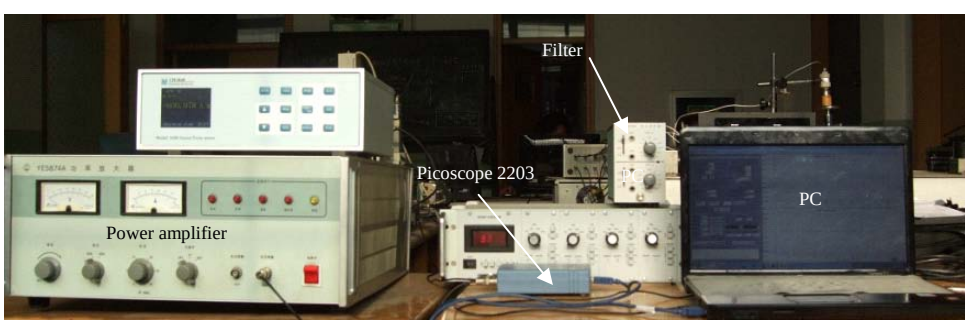

Fig. 3: Setup of GMA test system

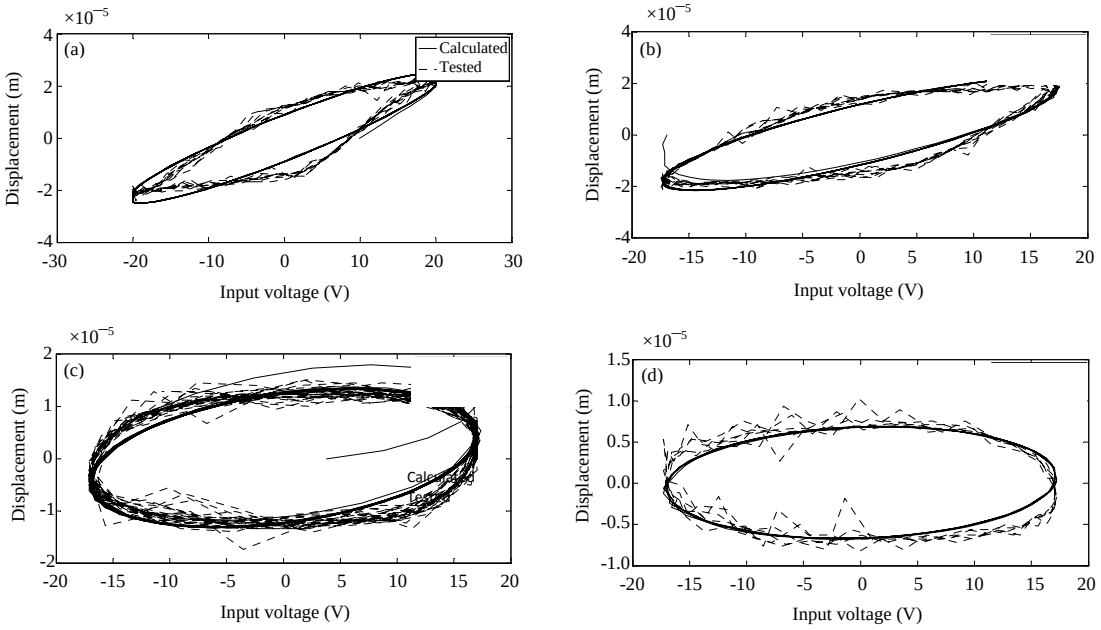

Fig. 4(a-d): Identification result in different frequencies at (a) 30, (b) 60, (c) 100 and (d) 200 Hz

this issue are mainly focus on the dynamic modeling of GMA with a series of given parameters (Wang and Zhou, 2013; He *et al*., 2013; Wenmei *et al*., 2012); some of the prior studies consider only the numerical identification of J-A model describing the ferromagnetic hysteresis behavior of GMM (Lederer *et al*., 1999; Wilson *et al*., 2001; Kis and Ivanyi, 2004; Toman *et al*., 2008; Trapanese, 2011); some studies deal with the quasi-static model of GMA without counting for the rate-dependent property of GMA (Cao *et al*., 2006; Zheng *et al*., 2007). Compared with these former studies, in this study, a dynamic model, combined with J-A model, quadratic model and the vibration transfer function, is proposed. The rate-dependent characteristic of GMA is taken into account. A modified PSO method, with its convergence speed and global optimization performances improved, is employed to identify the physical parameters of GMA, with considerable coincidence of calculated displacement and tested displacement, the effectiveness of proposed model and identification method are validated.

CONCLUSION

- A rate-dependent dynamic hysteresis model based on J-A model is established in this study considering the eddy current loss and abnormal loss
- A modified PSO method is employed to determine the coupled parameters of GMA, in order to provide an effective predict of output displacement of the actuator
- A system is established to test the output displacement of GMA, through experiments in different frequencies, the effectiveness of the proposed model and the identification method is validated

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