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Valve's Dynamic Damping Characteristics — Measurement and Identification

Ru Lai, Xiangdong Liu, Guoqiang Wu and Zhen Chen

Abstract— **This paper proposes a novel method to test the dynamic damping characteristics of valve. The testing system employs the vertical movement pattern, and has a suspension support structure. Force sensors are installed to measure the dynamic friction of the working valve directly. Making use of LuGre friction model and both adaptive genetic algorithm and chaos particle swarm optimization algorithm, the valve's dynamic damping parameters can be identified. Experiments have been carried out on a piston rod with a rubber ring and a steel cylinder. The results demonstrate the designed dynamic damping test system and the parameter identification algorithms are effective.**

I. INTRODUCTION

Valves are one of the most important and extensively used devices in aerospace, automotive, petrochemical and other industries. Since the working conditions of valve are usually very harsh, the valve's characteristics could seriously affect the operational performances as well as its working life span. Valve's friction characteristics, in most cases, are described only by its static Coulomb and viscous frictions. But by ignoring the dynamical friction can no longer meet the requirements of high speed and high precision control systems. Therefore, it is essential to measure the dynamic damping characteristics of valves for the purpose of friction compensation and valve design references.

Some papers investigate friction characteristics of valves, and present their friction testing systems [1]–[3]. Most of them obtain the friction characteristics of the valve by a system, in which an actuator drives the testing valve to move. By measuring the actuator's input voltage and the valve's output position, the system friction properties can be determined. However, in this way, the measured data often include the influences of some other factors of the system, such as the uncertainties of the motor and transmission links, etc. Direct and accurate measurement method for the valve's dynamic friction still need to be investigated.

The friction has been studied many years. More than 30 kinds of friction models have been proposed [4], [5]. They can be divided into two categories: the static and dynamic friction models. Static friction model does not reflect the increasing in static friction and the friction memory phenomenon. People used differential equations to describe the dynamic characteristics of friction, and considered the diversification in friction as the speed of response, and proposed a series of dynamic friction models. The most influential ones are: Dahl model, Mane model, Reset integrator model, and LuGre model [6]–[8]. As LuGre model can accurately describe the friction phenomenon comprehensively, in recent years many scholars have applied it to mechanical control systems.

Genetic algorithm has been used in parameter identification problems [9], [10]. In order to ensure the accuracy and convergence of the results, varied improved methods have been proposed. Among them there are adaptive genetic algorithm and particle swarm algorithm [11]–[13]. In the adaptive genetic algorithm, the probabilities of crossover and mutation are varied depending on the fitness values of the solutions to realize both the diversity of the population and the convergence capability. We present a chaos particle swarm algorithm, which combines chaos operator into inertia weighted particle swarm algorithm, to eliminate the maximum of particle velocity, as well as to prevent the local optimum.

This paper proposes a novel method to measure directly the dynamic damping characteristics of valves. First, the system configuration for testing dynamical characteristics of valve is introduced. Then, by employing LuGre friction model and both of adaptive genetic algorithm and chaos particle swarm algorithm, the dynamical parameters of the LuGre model have been identified. Finally, experiment results are demonstrated.

II. SYSTEM CONFIGURATION

A. Dynamic Damping Test System

Dynamic damping test system of valve consists of three parts: host computer, control cabinet and test-bed.

The main functions of host computer are sending commands for the movement of driving motors, receiving and processing relevant data, displaying the performances of the working valve on line, and parameter identification, etc.

The functions of the control cabinet are to communicate with the host computer, according to instructions from host computer to control the driving motor, and to sample analog and digital signals simultaneously.

The test bed is used to install the testing valve, sensors, and mechanical structure to support the equipment, which implements the operating environment for the testing valves. The composition of the system diagram is shown in Fig. 1.

From Fig. 1 we could see that the commonly used testing scheme measures the input voltage of the motor and output

Ru Lai is with the School of Automation, Beijing Institute of Technology, Beijing 100081, China. (Corresponding author, phone: +86-10-68912460; fax: +86-10-68913647; email: lairu@bit.edu.cn)

Xiangdong Liu, Guoqiang Wu, and Zhen Chen are also with the School of Automation, Beijing Institute of Technology, Beijing 100081, China. (email: xdliu@bit.edu.cn,wuguoqiang@126.com, chenzhen76@bit.edu.cn)

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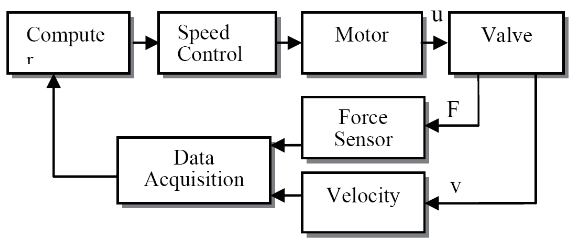

Fig. 1. Composition diagram of dynamic damping system

velocity/position of the valve. It is clear that the properties of the motor and mechanical transmission links are considered, which is difficult to be modeled accurately.

In our designed system, force sensors were installed in a suspension support structure, which contact with the test valve directly, that to measure the dynamic friction directly. By this designed structure, the influences of non-modeled factors in the system can be excluded, and the measured results are more accurate.

B. Installation of Test Bed

Dynamic damping test bed composes two movement driving systems. One is a DC PM linear motor driving system, which realizes the distances of 0-200 mm, frequency of 0-200 Hz movements. Another is a piezoelectric motor driving system, which completes the distances of 0-120 um, frequency of 200-1000 Hz movements.

Two driving motors are installed in vertical direction for the purpose of preventing the influences of the piston mass to the dynamic friction measurement.

The movement of the valve is direct driven by two motors to avoid the error produced by mechanical transmission links, thus to ensure the position measurement more accurate.

The dynamic friction between moving piston and cylinder of valve (in the experiment) was measured by 4 dynamic force sensors. In order to measure the friction more accurately, the cylinder was installed between a suspension support structure. The cylinder was fixed by 4 force sensors, and contacts only with the 4 force sensors. Therefore, the dynamic friction produced by valve's movement could be measured directly and accurately by force sensors to prevent the disturbances of other mechanical contacts.

C. Data Acquisition System

Data acquisition system involves the analogue signals of 4 force sensors, and the digital signals of the motor encoder. System synchronization interface technique was designed to reach simultaneous data acquisition. Three DAQ cards and an F/V module were adopted [14].

D. System Software

The software of the test system has been developed through LabVIEW. SQL database and Data socket technology are also adopted in the system. Matlab is used in parameter identification algorithms.

This test system can achieve the function of setting up the movement of motors, real-time sampling and monitoring, processing data, database management, parameter identification, etc.

III. LUGRE FRICTION MODEL

Many friction models have been studied and compared. LuGre model not only considers viscous friction and Coulomb friction, but also takes the static friction and Stribeck effect of the negative slope into account. Therefore, it is a more complete friction model which considered the full reaction to the friction mechanism of object movement.

LuGre model has the following formation

$$F = \sigma_0 z + \sigma_1 \frac{dz}{dt} + \sigma_2 v \tag{1}$$

$$\frac{dz}{dt} = v - \frac{|v|}{g(v)} z \tag{2}$$

$$g(v) = \frac{1}{\sigma_0}\left[F_c + (F_s - F_c)\mathrm{e}^{-(\frac{v}{v_s})^2}\right] \tag{3}$$

where σ_0 is the stiffness of bristles, N/m; σ_1 is the damping coefficient, Ns/m; σ_2 is the viscous coefficient, Ns/m; F_c is Coulomb friction, N; F_s is State friction, N. z is the average deflection of the bristles, m; v is the relative velocity between the two surfaces, m/s; v_s is Stribeck velocity, m/s; $g(v)$ is a positive and nonlinear function that related with physical conditions of the system. F_s, F_c, v_s, and σ_2 are generally called static parameters of the friction model, while σ_0 and σ_1 are recognized as dynamic parameters.

Since both the static and dynamic parameters are nonlinear, and coupling, it has no mature methods yet to estimate the parameters in LuGre model effectively.

In this paper, we present two parameter identification algorithms of adaptive genetic algorithm and chaos particle swarm algorithm. Both the static and dynamic parameters of the valve can be determined.

IV. PARAMETER IDENTIFICATION ALGORITHM

A. Adaptive Genetic Algorithm (AGA)

Genetic algorithm has been widely applied in parameter identification area. Recent years, many improved genetic algorithms have been developed to avoid local optimum and convergence [11].

In this paper, we used adaptive genetic algorithm to identify static and dynamic parameters in LuGre friction model. The operating procedure of adaptive genetic algorithm is shown in Fig.2.

In Fig. 2, most operations are the same with standard genetic algorithm. But the probabilities of crossover and mutation operators are taken to adaptive adjust.

Selection probability of individual

$$P(i) = \frac{q(1-q)^{r-1}}{1-(1-q)^n} \tag{4}$$

where q is the best individual, r sequence number of individuals, n population size.

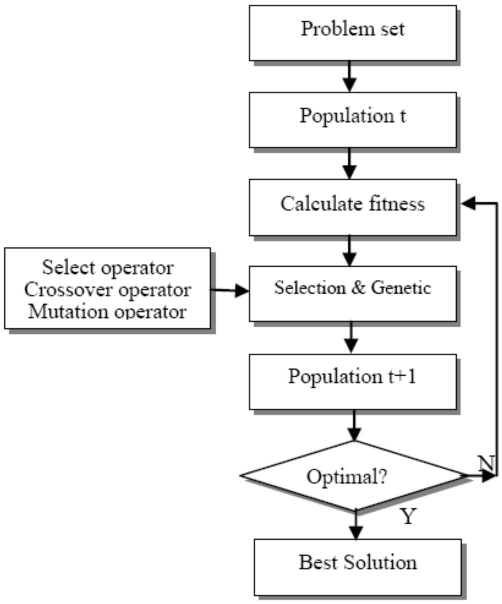

Fig. 2. Adaptive genetic algorithm flow chart

Crossover operator

$$\begin{cases} X^*(i) & = \lambda X(i) + (1-\lambda)X(i+1) \\ X^*(i+1) & = (1-\lambda)X(i) + \lambda X(i+1) \end{cases} \tag{5}$$

where $X(i)$, $X^*(i)$ are individuals before and after crossover. λ is (0,1).

Mutation operator

$$X^*(i) = \frac{\mathrm{Min}(i) + \mathrm{Max}(i)}{2} + \frac{\mathrm{Max}(i) - \mathrm{Min}(i)}{2}(\varphi - 0.5) \tag{6}$$

where $M_{max}(i)$ indicates maximum of $X^*(i)$, $M_{min}(i)$ minimum of $X^*(i)$, φ is random number of (0,1).

Here, the adaptive crossover probability P_c and the mutation probability P_m are set to

$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1}-P_{c2})(f-f_{ave})}{f_{max}-f_{ave}} & f \geq f_{ave} \\ P_{c1} & f < f_{ave} \end{cases} \tag{7}$$

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1}-P_{m2})(f-f_{ave})}{f_{max}-f_{ave}} & f \geq f_{ave} \\ P_{m1} & f < f_{ave} \end{cases} \tag{8}$$

where f_{max} is the best of individual fitness, f_{ave} is average of individual fitness, f is the individual who has the greater fitness between two crossover individuals.

M.Srinvivas [11] presents an adaptive probability of P_c and P_m. But P_c and P_m are zero for the solution with the maximum fitness. That causes the evolution nearly to stop. Here, we choose $P_{c1} = 0.9$, $P_{c2} = 0.6$, $P_{m1} = 0.1$ and $P_{m2} = 0.01$. Since the probabilities of P_{c2} and P_{m2} were set to non-zero, the best individual might not stop searching. This prevents the solution getting stuck into local optimal. While at the global optimal, the fitness value will be better than other solutions.

B. *Chaos Particle Swarm Algorithm (CPSA)*

1) Particle Swarm Algorithm: For the purpose of comparison, we also used a modified particle swarm algorithm to identify LuGre model parameters.

Particle swarm algorithm is an intelligent computation technique. It simulates the behavior of a school of flying bird. Every particle adjusts its position by its velocity in the space. The velocity of a particle depends both on its personal experience and other particles' experiences. The performance of each particle is measured according to a fitness function, which is related to the problem to be solved.

The particle swarm algorithm is as follow [12]

$$\begin{aligned} &X(i+1) = X(i) + V(i+1) \\ &V(i+1) = wV(i) + c_1 r_1 (P(i) - X(i)) + c_2 r_2 (G - X(i)) \\ &\quad V(i) = \frac{V(i)V_{\max}}{|V(i)|} \quad |V(i)| > V_{\max} \end{aligned} \tag{9}$$

where $X(i)$ is current position, $V(i)$ is current velocity, c_1 and c_2 are positive constants, r_1 and r_2 are random numbers of [0,1], w is inertia weight (0,1). $P(i)$ is the best position ever reached by the individual particle, while G the best position ever reached by the whole swarm.

In this inertia weighted particle swarm algorithm, as in [13], an inertia weight w is brought into the equation. The function of w is balancing the global search and local search. A large inertia weight value refers to a global search, while a small inertia weight value refers to a local search. It can be a positive constant or even a linear or nonlinear function of time. Since in our dynamic damping test system, the valve moves in as high as 1000 Hz frequency, the system state changes dynamically. Here, we took w as

$$w = 0.5 + Ran/2 \tag{10}$$

This w produces a number randomly varying between 0.5 and 1.0, with a mean of 0.75.

Comparing with the genetic algorithm, particle swarm algorithm is also an intelligent computation technique, and includes population, and evaluates by fitness function.

2) Chaos Particle Swarm Algorithm: Chaos is a kind of natural phenomenon, which has the characteristics of randomness and ergodicity. In order to prevent the problem of evolution stagnation, and ensure the convergence to the global optimum, we added a chaos variable into particle swarm algorithm.

Chaos variable is

$$Z(i+1) = 4Z(i)(1 - Z(i)) \quad 0 \leq Z(0) \leq 1 \tag{11}$$

where $z(0)$ is the initial value of chaos variable.

Chaos variable maps into problem space

$$X(i) = X_{\min} + (X_{\max} - X_{\min})Z(i) \tag{12}$$

Chaos variable with disturbance

$$Z^{/}(k) = (1-\alpha)Z(g) + \alpha Z(k) \tag{13}$$

where $Z(g)$ is a chaos variable by mapping optimum position of $X(g)$ into [0,1]. $Z(k)$ is the chaos variable after k iteration, $Z'(k)$ is the chaos variable plus disturbance, α is a disturbance of [0,1], m is an integer,

$$\alpha = 1 - (\frac{k-1}{k})^m \tag{14}$$

The disturbance strength depends on α. The greater α influences variable stronger, smaller α influences weaker. Therefore, using a chaos variable and disturbance ensures the convergence and robust in searching global optimum.

The procedure of the chaos particle swarm algorithm is as following:

Step 1. Initialize a population of particles with random positions and velocities in the problem space.

Step 2. Produce chaos variable.

Step 3. Map the chaos variable into individual in particle swarm space.

Step 4. Evaluate the desired fitness function values, and arrange the sequence of particles according to their individual fitness value.

Step 5. If the maximum iteration is reached, output the optimum value. Otherwise, turns to Step 6.

Step 6. Update the particles with chaos disturbance added to 25% inferior particles.

Step 7. Evolve new generation, and turns to Step 4.

C. Parameter Identification of LuGre Model

In LuGre model, F_s, F_c, v_s and σ_2 are static friction parameters and σ_0 and σ_1 are dynamic friction parameters.

Set the identification of parameters

$$x_d = [\sigma_0 \quad \sigma_1 \quad F_s \quad F_c \quad v_s \quad \sigma_2]^T \tag{15}$$

Objective function is

$$J = c_1 \sum_{i=1}^{N} e^2(x_d, t_1) + c_2 e\max|e(x_d, t)| \tag{16}$$

where c_1 and c_2 are weight coefficients.

For a moving object, there is

$$ma = u - F \tag{17}$$

where m indicates mass, a acceleration, u control input which is the output force of the linear motor, F denotes friction.

Assuming the control input of the valve system is

$$u = 1.1 \sin 5t \tag{18}$$

Define identification error as

$$F_e(x_d, t_i) = F(t_i) - F_1(x_d, t_i) \tag{19}$$

$$e(x_d, t_i) = s(t_i) - s_1(x_d, t_i) \tag{20}$$

where $F(t_i)$, $s(t_i)$ is the friction and displacement of the actual system at time of t. $F_1(x_d, t_i)$ and $s_1(x_d, t_i)$ are the model output friction and displacement at time of t.

Then,

$$F_1 = \sigma_0 z + \sigma_1 \frac{dz}{dt} + \sigma_2 \dot{s}_1 \tag{21}$$

$$\dot{z} = -\frac{\dot{s}_1}{g(\dot{s}_1)} z + \dot{s}_1 \tag{22}$$

$$\sigma_0 g(\dot{s}_1) = F_c + (F_s - F_c)\mathrm{e}^{-(\dot{s}_1/\dot{s}_s)^2} \tag{23}$$

Set the objective function as

$$J(x_i) = \frac{1}{N} \sum_{i=1}^{N} (F_i - F_i^{/})^2 \tag{24}$$

Fitness function as

$$f(x_i) = \max[J(x_i)] - J(x_i) \quad i = 1, 2, \cdots, M \tag{25}$$

V. EXPERIMENT RESULTS

A. Experimental Condition

The experiments have been carried out by the dynamic damping test system that we implemented. The computer of the system is an IPC with CPU of Intel 2 core, 2.13 GHz, memory. The dynamic forces and the position signals were sampled simultaneously with the sampling frequency of 1000 Hz for linear motor system, and 50000 Hz for piezoelectric motor system. The communication between IPC and the controller is by LAN of 100 Mbps.

The experiments were designed to simulate the state of a working valve. The testing piece consists of a piston with a contacting rubber ring, and a steel cylinder. The dynamic friction between the rubber ring and the surface of the steel cylinder was measured.

The movement patterns of testing valve include sine function, triangle function, and trapezoid function under different frequencies and amplitudes.

There are two movement driving systems. One is a DC PM linear motor driving system, which realizes the distances of 0-200 mm, frequency of 0-200 Hz movements. Another is a piezoelectric motor driving system, which completes the distances of 0-120 um, frequency of 200-1000 Hz movements.

The purpose of the experiment is to test the dynamic friction of valve, and to identify its friction parameters under different movement conditions, which demonstrate the dynamic damping characteristics of testing valve.

B. Experimental Results

1) Result by AGA: Figure 3 and Fig. 4 show experiment results. The blue line is the measured data from force sensors, while the red line is calculated data by bringing identified parameters into LuGre model. The valve's movements of 0-200 Hz were driven by linear motor, while the movements of 200-1000 Hz were driven by piezoelectric motor.

From Fig. 3 and Fig. 4, the identified parameters could describe valve's characteristics quite accurate. However, when valve moves in low frequency, the identified error is greater than in high frequency. Also, there is a lag in the calculated value. That is because the LuGre model in (3) and (23) has an exponent term, which may cause delay. The results demonstrate the LuGre model parameters identified by adaptive genetic algorithm are effective.

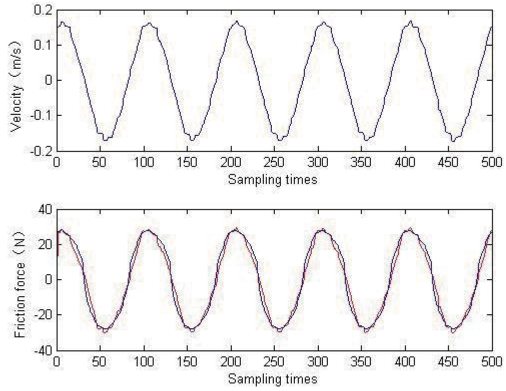

Fig. 3. Linear motor drive with sin input of 4Hz (AGA)

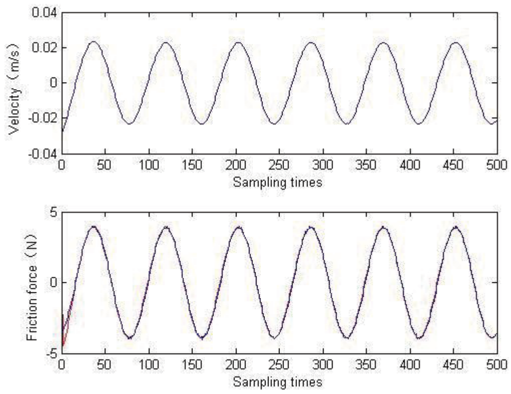

Fig. 4. Piezoelectric motor drive with sin of 600Hz (AGA)

Table 1 shows the data of friction parameters identified by adaptive genetic algorithm on some other frequencies.

Data of 4 Hz and 10 Hz were taken by linear motor, and 300 Hz and 600 Hz were taken piezoelectric motor. F_c, F_s, v_s, and σ_2 are static parameters, σ_1 and σ_0 are dynamic parameters.

When the valve moves in low frequency, six friction parameters are nearly consistent. But when the valve moves in high frequency, as 600 Hz, the identified parameters change a lot. Especially, dynamic parameter σ_0, which shows the stiffness characteristics. The reason might be when valve moves in so high frequency of 600 Hz, and so short travel distance of 60 um, the rubber ring might not actually move, only make some deformation. Since the motion modes are different, the dynamics it demonstrated should be different.

TABLE I

LUGRE MODEL PARAMETERS IDENTIFIED BY AGA

(Hz)	F_c	F_s	v_s	σ_2	σ_1	σ_0
4	5.27	34.43	0.021	48.55	138.83	4457.9
10	5.79	39.17	0.017	48.66	136.83	4286.02
300	5.88	37.6	0.0053	48.92	112.92	2006.5
600	7.4	43.2	0.003	7.43	162.3	344.96

2) Result by CPSA: For the purpose of comparison, we also used chaos particle swarm algorithm to identify the six friction parameters in LuGre model. The experiment data are the same with adaptive genetic algorithm.

Figure 5 and Fig. 6 show the results. The blue line is the measured data from force sensors, while the red line is calculated data by bringing identified parameters into LuGre model.

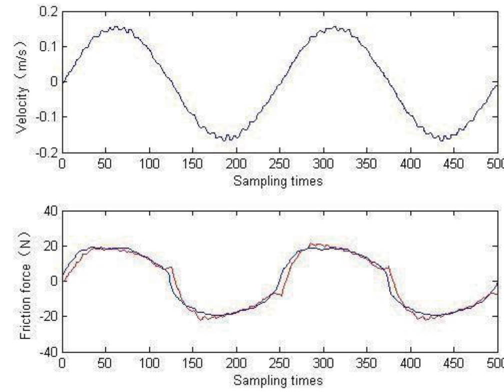

Fig. 5. Linear motor drive with sin input of 4Hz (CPSA)

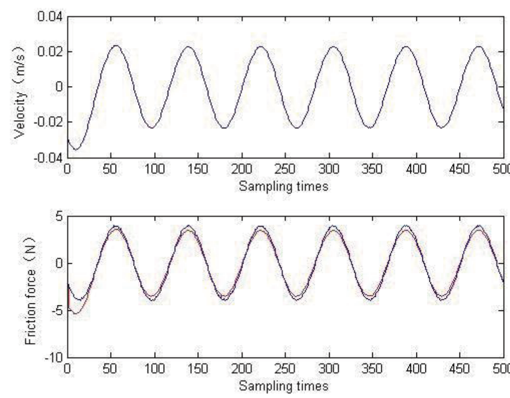

Fig. 6. Piezoelectric motor drive with sin of 600Hz (CPSA)

Table 2 shows the data of friction parameters identified by chaos particle swarm algorithm on some other frequencies.

Fig. 7 shows the parameters convergence process by adaptive genetic algorithm and chaos particle swarm algorithm. We could see AGA demonstrated better accuracy, while CPSA has faster convergence speed.

Comparing Table 1 and Table 2, the identified parameters by both algorithms are agreed. This also verified the correctness of two identification algorithms.

Both identification algorithms are successful to achieve acceptable accuracy of the results, convergence to global optimum, and work steady.

VI. CONCLUSION

This paper presents a novel dynamic damping test system we developed for measuring dynamic damping of valves. By

TABLE II

LuGRE MODEL PARAMETERS IDENTIFIED BY CPSA

(Hz)	F_c	F_s	v_s	σ_2	σ_1	σ_0
4	5.28	31.91	0.012	46.58	134.72	4492.6
10	5.21	39.46	0.018	47.53	132.96	4723.8
300	6.93	39.06	0.0064	49.26	106.28	1974.5
600	6.8	55.7	0.002	7.94	138	382

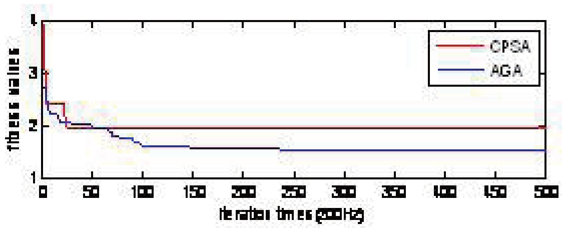

Fig. 7. Convergence process of AGA and CPSA (200Hz)

obtaining friction and velocity data, the dynamic damping parameters of valve could be identified based on adaptive genetic algorithm and chaos particle swarm algorithm. Experiment results demonstrate the effectiveness of designed system and algorithms. This system can be use in testing dynamic characteristics of valve for the purpose of control compensation and valve design reference.

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