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Parameter Identification for Dynamic Damping System Based on Genetic Algorithm

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Abstract

In order to obtain the damping coefficient and other parameters that influence the dynamic features of the valve, this paper employs the "LuGre friction model" to describe the precise dynamic and the static features, and presents a new one-step identification method for the parameter identification of LuGre friction model through the optimization by genetic algorithm. With the properly selected objective function, four static parameters and two dynamic parameters can be obtained simultaneously by the MATLAB programming language. The proposed method is proved effective through the verification of the identified parameters.

Key words

Damping, Friction model, Genetic algorithm, Parameter identification.

1. Introduction

Valves are important, indispensable equipment in the aerospace, petrochemical, coal chemical, and other industries. Owing to the harsh working conditions, it is inevitable for the friction pair of the valve to suffer wear and tear. The wear of valve friction pair severely affects the sealing effect, operational performance and life span of the valve. With the in-depth research on friction and the improved requirements on the dynamics of mechanical systems, it is no longer reasonable to neglect joint friction or replace it simply with the equivalent viscous damping. This calls for the establishment of a proper friction model and the identification of the friction parameters in mechanical systems, the preconditions for dynamic analysis and control of mechanical systems.

The importance of building an accurate mathematical model for nonlinear friction systems is self-evident no matter from the perspective of understanding the friction phenomenon or in the view of offsetting the friction-induced damages and improving system performance. Therefore, friction modelling has been extensively explored by scholars at home and abroad. So far, more than 30 kinds of friction models have been proposed [1]. These models fall into two categories: the static model and the dynamic model. Models in the first category do not reflect the increase in static friction or the friction memory phenomenon [2].

Some scholars used differential equations to describe the dynamic features of friction and attributed the difference in friction to the speed of response. Following this train of thought, these scholars put forward a series of dynamic friction models. The most influential ones inlclude: Dahl model, mane model, reset integrator model, Bliman and Sorine model [3] and LuGre model [4-6].

Nevertheless, there is no mature method to solve the LuGre model parameters identification problem. In that model, it is relatively easy to identify the static parameters but immensely difficult to ascertain the dynamic ones. The difficulty rises from the fact that the LuGre model is a non-linear system with unmeasured internal state z and coupling effect between the dynamic and static parameters. In Literature [7], the second-order linear description is adopted to estimate the two dynamic parameters by the frequency-domain identification experiment. However, the identification based on the partial linearization method hinges on the selection of initial parameters, making it even harder to ensure accuracy and convergence.

Recent years has seen domestic and foreign scholars developing a lot of identification methods [8] for non-linear systems by applying genetic algorithm to parameter identification [9]. In light of this trend and the ability of the LuGre model to accurately describe the friction phenomenon, this paper presents a parameter identification method of LuGre model based on genetic algorithm [15-17].

2. System Structure and Feature Implementation

The dynamic damping test system is mainly for the purpose of measuring the frictional features in the simulated cylinder packing ring system. It simultaneously measures the velocity affecting the friction features and dynamic damping features. For the maximum similarity between the simulator and the actual condition, the working conditions should be reconstructed with multiple subsystems.

The dynamic damping test system consists of three parts: host computer, console, and test bench (Figure 1).

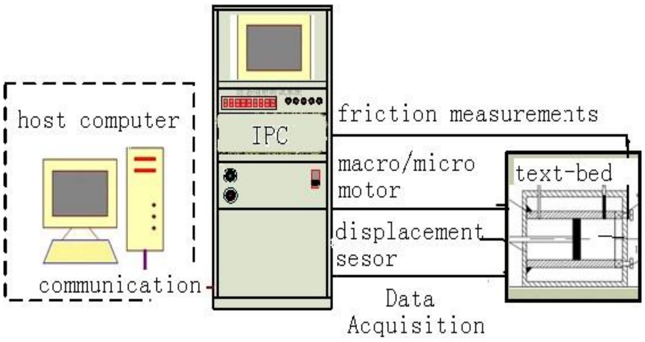


Fig.1. Dynamic damping tests system components

In the dynamic damping test system, the host computer is mainly responsible for data processing and computing, displaying performance indices, sending commands to the console according to functions, receiving relevant measurement data, and displaying image curves. The console is mainly responsible for communicating with the host computer, controlling the test bench drive motor according to the commands from the host computer, acquiring and processing data, etc. The test bench is mainly responsible for installing the device and simulating the operating environment of the objects and it is composed of a motor drive system and a data acquisition system.

Figure 2 is the sketch map of the composition of the dynamic damping test system. Both the main components of the system and the relationship between the test machine and the various subsystems are displayed in this sketch map.

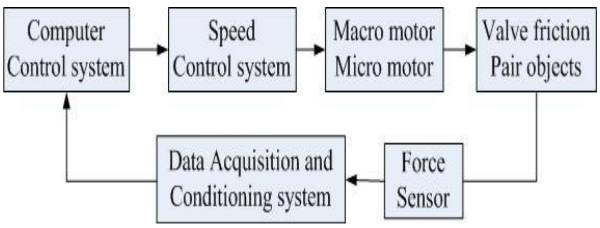


Fig.2. Composition diagram of the dynamic damping

The data acquisition system involves both the analog signals of force sensor and temperature sensor, and the digital signal of grating sensor. The measurement variables include friction, pressure and velocity.

The host computer realizes real-time monitoring and dynamic damping valve test through LabVIEW. The key measurement variables of various signals are monitored in real time to achieve real-time display and analysis. The linear motor and piezoelectric motor send commands through the host computer, and receive the returned data for index calculation and test. The data analysis and historical data are preserved and displayed for further use.

2.1 Lugre Friction Model

In order to obtain the valve's damping coefficient, it is necessary to study the features of the friction simulation model and the algorithms. Among the various friction models in existence, the most popular ones are the Karnopp model, LuGre model and integrated model. In a brief overview of static friction modeling and simulation, Shi [10] compared the simulation results of three friction models (i.e. Coulomb friction model, Karnopp model, Reset Integrator model), pointing out that Karnopp model outperformed the other two models in simulating the friction features at the relative velocity of zero. Wang [11] simulated the static friction at the launch of the system with the feed-forward channel of Saturation Module, and emulated the nonlinear static friction in viscous phase by Simulink. MsMadi et al. [12] put forward a parameter identification method based on interval analysis of bounded error for the identification of LuGre friction model parameters. Janswevers et al. [13-14] examined the pre-sliding and sliding phases separately, drew the relation curves between the friction torque and speed, and obtained the static and dynamic friction model parameters by curve fitting method.

Proposed by Canudas de Wit C, the LuGre model is a typical dynamic model. It can be simplified as follows:

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

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

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

Where z is the average deflection of the bristles; $\boldsymbol{\sigma_1}$ is the damping coefficient, Ns/m; $\boldsymbol{\sigma_2}$ is the viscous coefficient, Ns/m; $\mathbf{F_c}$ is Coulomb friction; $\mathbf{F_s}$ is static friction; V is the relative velocity between the two surfaces. The function g(v) describes the Stribeck effect. Overall, $\mathbf{F_c}$, $\mathbf{F_s}$, $\mathbf{v_s}$ and $\boldsymbol{\sigma_2}$ are static friction parameters while $\boldsymbol{\sigma_0}$ and $\boldsymbol{\sigma_1}$ are dynamic friction parameters.

LuGre model is a complete friction model, reflecting the full reaction to friction movement. It not only considers the viscous friction and Coulomb friction, but also the static friction and Stribeck effect (Figure 6) of the negative slope. The phenomenon of pre-slip displacement (Figure 7) can be simulated through the combination of (1), (2), (3) and (4).

3. Parameter Identification

3.1 Identification of Static and Dynamic Parameters

The abovementioned LuGre model deals with the expression of linear motion:

$$ma = u - F \tag{4}$$

Where m is mass, kg; a is acceleration, m/s2; u is traction, N; F is friction, N. The corresponding time of velocity can be acquired according the input of the system control u=1.1 sin5t. The identification parameters are set as $\boldsymbol{x_d} = [\boldsymbol{\sigma_0}, \boldsymbol{\sigma_1}, \boldsymbol{F_c}, \boldsymbol{F_s}, \boldsymbol{v_s}, \boldsymbol{\sigma_2}]^{\boldsymbol{T}}$. The identification error is defined as:

$$F_e(x_d, t_i) = F(t_i) - F_1(x_d, t_i) \tag{5}$$

$$e(x_d, t_i) = s(t_i) - s_1(x_d, t_i) \tag{6}$$

Where $F(t_i)$ and $s(t_i)$ are the output displacement and friction of the actual system at time of t_i, respectively; $F_1(x_d, t_i)$ and $s_1(x_d, t_i)$ are the output displacement and friction consisting of the identification parameters of the system model at time of t_i, respectively. Thus, we have the following equations:

$$m \cdot a_1 = u - F_1 \tag{7}$$

$$F_1 = \sigma_0 z + \sigma_1 \frac{dz}{dt} + \sigma_2 \dot{s}_1 \tag{8}$$

$$\dot{z} = -\frac{|\dot{s}_1|}{g(\dot{s}_1)} z + \dot{s}_1 \tag{9}$$

$$\sigma_0 g(\dot{s}_1) = F_c + (F_s - F_c) e^{-(\dot{s}_1/\dot{s}_s)^2} \tag{10}$$

The objective function is defined as:

$$J = c_1 \sum_{i=1}^{N} e^2(x_d, t_i) + c_2 e \max\{|e(x_d, t_i)|\} + c_3 \sum_{i=1}^{N} Fe^2(x_d, t_i) + c_4 Fe \max\{|e(x_d, t_i)|\} \tag{11}$$

Where c_1, c_2, c_3 and c_4 are weight coefficients.

During the identification process, it is necessary to measure the output displacement of the actual open-loop system at different times, and the corresponding friction at each moment. The identification error at different times can be obtained by measuring the displacement, the friction with the output displacement, and the friction composed of the identification parameters of the system model.

The objective function is established on the maximum error of displacement and the maximum error of friction. At each iteration, the two errors are calculated on the computer, aiming to minimize the maximum error and let the estimates converge to the true values in a more efficient manner.

Compared with the one-step identification, the two-step identification estimates the four static parameters $\boldsymbol{F_c}, \boldsymbol{F_s}, \boldsymbol{v_s}$ and $\boldsymbol{\sigma_2}$ via Stribeck curve first. Substitute $\frac{dz}{dt}$=0 into (1), (2) & (3), we can get the steady state friction:

$$F_s = \sigma_0 z_s + \sigma_2 v \tag{12}$$

$$z_s = g(v)\,\mathrm{sgn}(v) \tag{13}$$

Substitute (3) & (6) into (5):

$$F_S = \left[F_c + (F_s - F_c) e^{-(\frac{v}{v_s})^2} \right] \mathrm{sgn}(v) + \sigma_2 v \tag{14}$$

Where the curve between friction and velocity is called “the steady-state Stribeck curve”. Next, two dynamic parameters $\boldsymbol{\sigma_0}$ and $\boldsymbol{\sigma_1}$ are estimated.

Set the static parameter identification vector x_s=($\boldsymbol{F_c}, \boldsymbol{F_s}, \boldsymbol{v_s}, \boldsymbol{\sigma_2}$) and define identification error as:

$$e(x_s, v_i) = u_i - F_S(v_i) \tag{15}$$

Set the objective function as:

$$J = \frac{1}{2}\sum_{i=1}^{n} e^2(x_s, v_i) \tag{16}$$

Static parameters identification: acquire the parameter vector x to minimize the objective function J.

Dynamic parameters identification: identify $\boldsymbol{\sigma_0}$ and $\boldsymbol{\sigma_1}$ by the limit cycle oscillation curve [13]. Set the objective function as:

$$J = c_1\sum_{i=1}^{N} e^2(x_d, t_i) + c_2 e\max\{|e(x_d, t_i)|\} \tag{17}$$

Where $\boldsymbol{\sigma_1}$ and $\boldsymbol{\sigma_2}$ are weight coefficients.

3.2 Genetic Algorithm Design

The identification of static and dynamic parameters is optimized by genetic algorithm [8-9]. Specifically, individual parameter vector is identified in a binary encoding format, the roulette selection is performed, the uniform crossover is conducted, and the mutation is carried out using the bit string operator. Figure 3 describes the operation flow of the genetic algorithm[17].

The fitness function is set as:

$$\begin{cases} C_m = \max\{J(x_i)\} \\ f(x_i) = C_m - J(x_i) \end{cases} i = 1, 2\cdots M \tag{18}$$

Where Cmax=max{J(xi)} ensures the non-negativity of the fitness function.

The algorithm operates in the following steps:

(1) Initialization: Set the generation counter as 0→t, define the maximum number of generations as T, and randomly generate N friction model parameters to form the initial population P (0);

(2) Individual evaluation: Calculate population p (t) for each set of parameters of the fitness value;

(3) Selection: Process the population with the selection operator;

(4) Crossover: Process the population with the crossover operator;

(5) Mutation: Process the population with the mutation operator. After the selection, crossover and mutation of population p (t), the next-generation population p (t+1) is acquired.

(6) Termination: If $\mathbf{t} \leq \mathbf{T}$, then t+1→t; go back to (2). If t>T, then the individual with the greatest fitness is outputted as the optimal solution; terminate the calculation.

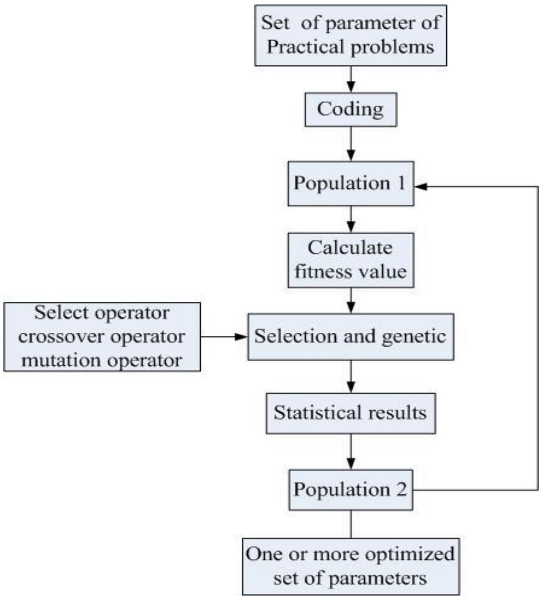
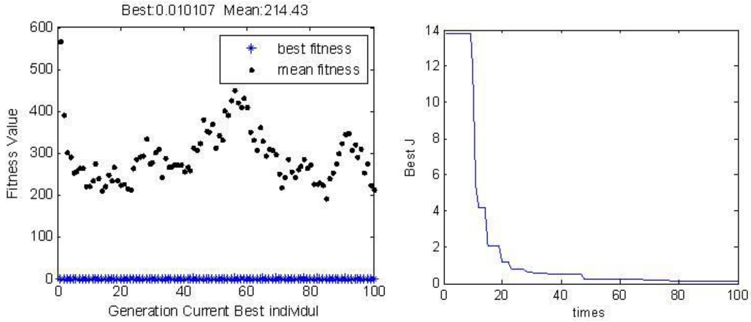


Fig.3. Genetic Algorithms operate flow process chart

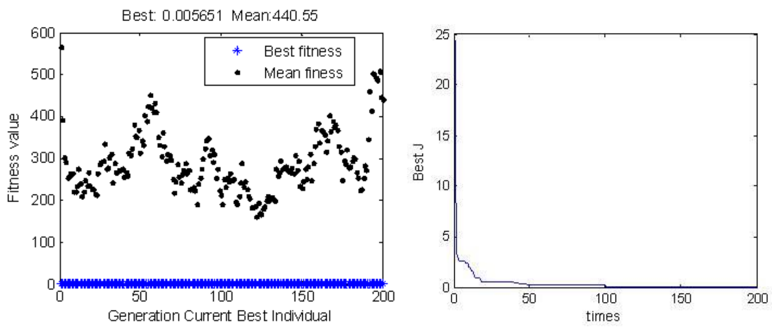
4. Simulation Results and Analysis

The genetic algorithm is stochastic, that is, it generates random probability. The result and convergence speed differ from operation to operation. With the continuous evolution from generation to generation, the results ultimately converge to the most adaptive individuals, thus forming the optimal solution.

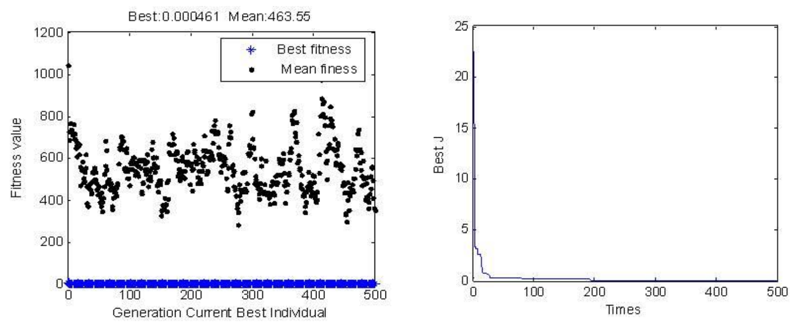
In figure 4, the subgraphs (a), (b) and (c) list the fitness values of the 100-th, 200-th and 500-th generations, respectively. The population size M is 50; the crossover probability P is 0.9, and the mutation probability P is 0.05.



(a) 100 iterations



(b) 200 iterations



(c) 500 iterations

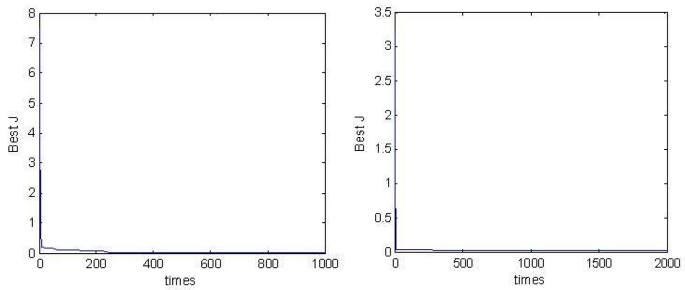
Fig.4. Situation of different iterations

Table 5-1 compares the minimum fitness values of the three generations obtained by the genetic algorithm. It can be seen that the fitness value is reversely proportional to the number of generations, and the algorithm results are converging.

Tab.5-1. Comparison of fitness value

Iterations	100 Generation	200 Generation	500 Generation
Minimumalue	0.010107	0.005651	0.000461

In Figure 5, the subgraphs (a) and (b) in Figure 5 present the parameter identification results of the 1,000-th and 2,000th generations, respectively. The optimal fitness values of the two generations are 0.00006311 and 0.0000020783. Considering that the fitness value of the 500-th generation is 0.000461, it is obvious that the fitness value decreases with the increase in the number of generations. According to Table 5-2, the parameter identification errors of the 1000th generation are 0.058%, 1.22%, 0.15%, 9.27%, 10%, and 5.57%. Despite the improved state of some parameters, the unsatisfactory estimated value call for further iterations. The identification value of the 2,000th generation is close to the true value with parameter identification errors of 0.0287%, 1.07%, 0.93%, 2.64%, 2% and 2.775%. The results show that the evaluation parameters and identification results are valid and satisfactory.



(a) 1000 iterations (b) 2000 iterations

Fig.5. The optimizing process of the objective function

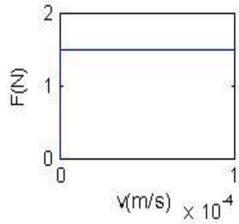


Fig.6.Stribeck Cure

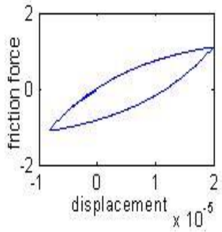


Fig.7. The phenomenon of pre-slip displacement

Tab.5-2. Comparison of identification values of different generations

Parameter	Actual value	Identification value (500 generation)	Identification value (1000 generation)	Identification value (2000 generation)
$\boldsymbol{\sigma_0}$	10^5	99891.5632	99942.2754	100028.7287
$\boldsymbol{\sigma_1}$	316	340.2324	319.8685	319.3825
$\boldsymbol{F_s}$	1.5	1.4785	1.4985	1.5093
$\boldsymbol{F_c}$	1	1.5427	1.0927	0.9736
$\boldsymbol{v_s}$	0.001	0.0019	0.0011	0.00098
$\boldsymbol{\sigma_2}$	0.4	0.4469	0.4223	0.4111

Table 5-3 compares the simulation parameters of one-step identification with those of two-step identification. We can see that the both of the two identification methods satisfy the identification requirements; one-step identification is able to achieve the identification accuracy of two-step identification. In the actual system, however, the controller parameters of the two-step identification method have to be adjusted, making it hard to maintain accuracy. The timeconsuming, labor-intensive two-step method inevitably complicates the experiment conditions. Although more number of generations is needed to identify the true value, the one-step identification method has a clear edge over the other method as it uses computer to do most of its work, saving manpower and resources.

Tab.5-3. The comparison of identification value between two-step identification and one-step identification

parameter	actual value	two-step	one-step
$\boldsymbol{\sigma_0}$ [N/m]	10^5	100028.7287	99906.8963
$\boldsymbol{\sigma_1}$ [N_s/m]	316	319.3825	319.1326
$\boldsymbol{F_s}$ [N]	1.5	1.5093	1.5000
$\boldsymbol{F_c}$ [N]	1	0.9736	1.0212
$\boldsymbol{v_s}$ [m/s]	0.001	0.00098	0.0010
$\boldsymbol{\sigma_2}$ [N_s/m]	0.4	0.4111	0.4046

Conclusion

Focusing on the dynamic damping test system, this paper establishes a friction model based on dynamic LuGre electromechanical servo system, and presents a new one-step identification method for the dynamic parameters of LuGre model through the optimization by the genetic algorithm. The proposed method can obtain static and dynamic friction parameters simultaneously. Compared with two-step identification method, the one-step identification method is obviously superior in that it reduces the steps and difficulty in the identification of static and dynamic parameters in the experimental static friction model, and that it overcomes the obstacle rising from the coupling effect between the static and dynamic parameters and improves the accuracy. Therefore, the proposed method boasts significant practical value for projects.

Acknowledgements

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