A METHOD OF SYSTEM IDENTIFICATION AND ITS APPLICATION IN HVAC SYSTEMS

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ABSTRACT
The operation effect of industrial process is largely determined by the automatic control system. In the conventional control process, the Proportional Integral and Derivative (PID) parameters need to be set according to the engineering experience. Not only is the control precision not enough, but also the robustness is poor. The performance of PID control based on the system transfer function is relatively good. However, it is usually limited by the accuracy of transfer functions. In this paper, a method based on PSO is studied for the identification of Heating, Ventilating and Air Conditioning (HVAC) system. By simplification the transfer function as a second order plus dead time model, using Particle Swarm Optimization (PSO) algorithm optimizes the parameters of the model to obtain the minimum differentiation between the outputs of the system and the model. Two examples are given to show this method is simple and results are accurate.

KEYWORDS
System identification; PSO; Transfer function; Second-order plus dead-time model.

INTRODUCTION
As it is well known, in many fields of process industry, PID controller is the most widely used control algorithm (Skogestad S 2001). It can date to 1890s governor design (Bennett S 1984, Bennett S 1993) and has been around for a long time. Today, more than 90% of all controllers are PID (Åström K J and Hägglund T 2001). This widespread application of PID in process industry can be result from their simplicity and ease of re-tuning on-line (Astrom K J 1995).

In fact, there are two methods to determine parameters of PID. One is called engineering experience tuning method which is depended on rich experience of an engineer. The other is tuning rules based on transfer function of the objective system

(Ziegler J G and Nichols N B 1942, Cohen G H and Coon G A 1953, Tyreus B D and Luyben W L 1992, Ho W K et al. 1998). Though the performance of the second method is always better than that of the first one, to find a precise transfer function of the tuning system is really a difficulty. Only three parameters although the PID controller has, it is not easy to find excellent values for them without a systematic procedure. For the most part, a visit to a process factory will usually demonstrate that a large number of the PID controllers work with poor performance. The reasons of this phenomenon could be attributed to lack of experience, low accuracy of the first tuning method, poor robustness of PID values, complexity of an industry system and unseemliness of the transfer function.

The process of investigation of a transfer function by using a mathematical model, as shown in Fig.1, to describe the system over a wide operation range is called system identification which acts as foundation of control theory. A great number of papers focus on the method of system identification (Hsia T C 1977, Ljung L 1998, Sjöberg J and Zhang Q 1995, Ljung L 1998, Ding F and Chen T 2004)and the similarity of them is the adoption of inverse matrix. As we know, the large calculation amount, long computing time and high demands on compute devices are fatal shortages of these kinds of method.

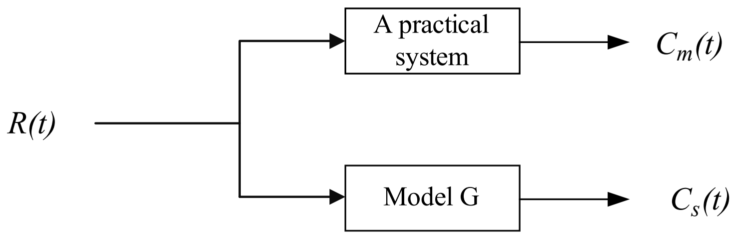

Fig.1 *Identification principle*

With the development of intelligent algorithms, such as Simulated Annealing (SA) (Kirkpatrick S 1984, Szu H and Hartley R 1987, Hwang C R 1988, Ingber L 1989, Eglese R W 1990), Genetic Algorithm (GA) (Mosetti G et al. 1994, Houck C R et al. 1995, Beasley J E and Chu P C 1996), Artificial Neural Networks (ANNs) (Hopfield J J 1988, Zurada J M 1992, Patterson D W 1998, Yao X 1999, Dayhoff J E and DeLeo J M 2001, Yegnanarayana B 2009), they are used more and more widely. An approach of system identification based on PSO is proposed and the application of this method is explored in this paper. Giving two examples of this identification method, it is concluded that the system identification based on PSO has stronger adaptability and better robustness.

METHODOLOGY

1. BASIC IDEA OF SYSTEM IDENTIFICATION

1.1 TRANSFER FUNCTION STRUCTURE OF MODEL G

The transfer function structure is pretty complex and more than fourth-order model. It will consume much time and computational equipment expense to identify such complicated function. In consideration of precision demands and calculating speed, the transfer function structure of model G is second-order plus dead-time model.

$$G(s)=\frac{k}{(\tau_1 s+1)(\tau_2 s+1)}e^{-\theta s} \tag{4}$$

where τ_1、τ_2、k and θ are identification parameters.

1.2 OUTPUT OF MODEL G

Real-number encoding was utilized in this paper. With the unit step signal input and a second-order plus dead-time model, the output could be represented as:

$$C_m(s)=R(s)\times G(s)=\frac{1}{s}\cdot\frac{k}{(\tau_1 s+1)(\tau_2 s+1)}e^{-\theta s} \tag{5}$$

After the Laplace inverse transform of equation (5), in time domain, the output function of model G is presented as following:

$$C_m(t)=0\ ,\ t<\theta \tag{6}$$

$$C_m(t)=k\times\left[1+\frac{\tau_1\tau_2}{\tau_2-\tau_1}\times\left(\frac{1}{\tau_2}e^{-\frac{t-\theta}{\tau_1}}-\frac{1}{\tau_1}e^{-\frac{t-\theta}{\tau_2}}\right)\right]\ ,\ t\geq\theta \tag{7}$$

1.3 OBJECTIVE FUNCTION

When estimating values of transfer function parameters of model G are optimal, output curves of $C_s(t)$ and $C_m(t)$ should be overlap mostly. Draw lessons from the concept of statistical sample standard deviation, output sample standard deviation S_{value} and slope sample standard deviation S_{slope} are defined.

$$S_{value}=\sqrt{\frac{\sum_{t=0\cdot t_f}^{t_n\cdot t_f}(C_s(t)-C_m(t))^2}{t_n-1}} \tag{8}$$

where t_f is system output time step; t_n is number of system output time step; $C_s(t)$ and $C_m(t)$ are the system output value and calculated value at t point.

$$S_{slope}=\sqrt{\frac{\sum_{t=1\cdot t_f}^{t_n\cdot t_f}(K_s(t)-K_m(t))^2}{t_n-2}} \tag{9}$$

where t_f is system output time step; t_n is system output time steps; $C_s(t)$ and $C_m(t)$ are the system output value and calculated value at t point. $K_s(t)$ and $K_m(t)$ are the slope values of system and model G during a particular time period of $(t\text{-}t_f)$. The calculated formula of $K(t)$is:

$$K(t)=\frac{C(t)-C(t-t_f)}{t_f} \tag{10}$$

The objective function used in this paper is:

$$F=S_{value}\times S_{slope} \tag{11}$$

2. PSO USED IN SYSTEM IDENTIFICATION

2.1 BRIEF INTRODUCTION OF PSO

In 1995, when they were studying bird behaviors of searching food, American psychologist Kennedy and electrical engineer Eberhart found that each member could benefit from all the other members' discoveries and flight experiences by sharing information between individuals. PSO is put forward based on this (Eberhart R C and Kennedy J 1995). This is another kind of swarm intelligence algorithm after ant colony algorithm (ACO) and widely researched and applied in many fields (Song M P and Gu G C 2004, Barrera J and Coello C A C 2009, García-Gonzalo E and Fernández-Martínez J L 2012).

In PSO each potential solution for an optimization problem is viewed as a particle without mass and volume in the search space. A number of particles form a population. Every particle's performance depends on the objective function of the optimization problem. Each particle then determines its movement through the search space by combining some aspect of the history of its own current and best (best-fitness) locations with those of one or more members of the swarm, with some random perturbations. The next iteration takes place after all particles have been moved. Eventually the swarm as a whole, like a flock of birds collectively foraging for food, is likely to move close to an optimum of the fitness function. For example, the position and velocity of particle i could expressed as:

$$X_i(t)=[x_{i,1}(t),x_{i,2}(t),\ldots,x_{i,D}(t)] \tag{12}$$

$$V_i(t)=[v_{i,1}(t),v_{i,2}(t),\ldots,v_{i,D}(t)] \tag{13}$$

By comparing the fitness value of the objective function of each particle, the best position of each particle $P_{best\,i}(t)=[p_{i,1}(t),p_{i,2}(t),\ldots,p_{i,D}(t)]$ and the best position in the group P_g are obtained. In the next iteration, the particle is updates its speed and position according to the following formulas:

$$v_{i,j}(t+1)=wv_{i,j}(t)+c_1r_1\left[p_{i,j}(t)-x_{i,j}(t)\right]+c_2r_2\left[p_{g,j}(t)-x_{i,j}(t)\right] \quad (14)$$

$$x_{i,j}(t+1)=x_{i,j}(t)+v_{i,j}(t+1),\ \ i=1,\ldots,n;j=1,\ldots,D \quad (15)$$

where w is inertia factor, c_1 and c_2 are positive acceleration constants, r_1 and r_2 are random numbers between 0 and 1.

2.2 IMPLEMENTATION PROCESS OF SYSTEM IDENTIFICATION BASED ON PSO

1) Initialize a population array of particles with random velocities and positions on D dimensions in the search space
2) For each particle, the position information initialized in process 1) is stored in $P_{best,i}$. The best $P_{best,i}$ is viewed as P_g
3) **loop**
4) Calculate output of models and fitness value of objective function according to the position of each particle
5) Compare fitness evaluation of a particle with its $P_{best,i}$. If current value is better than $P_{best,i}$, then set $P_{best,i}$ equal to the current location
6) Compare particle's $P_{best,i}$ with P_g. If $P_{best,i}$ is better than P_g, then P_g is replaced by $P_{best,i}$
7) Update position and velocity of each particle according to Equs (14) and (15)
8) If a criterion is satisfied (usually a sufficiently good fitness value or a maximum iteration), exit loop
9) **End loop**

SIMULATION EXAMPLE

In fact, the transfer function of an object in an HVAC system is nonlinear, complex and high-order. Also, noise must be taken into account.

Example 1. The system structure is a fourth-order without time delay model:

$$G(s)=\frac{5}{(5s+1)(10s+1)(20s+1)(30s+1)} \quad (16)$$

Under the conditions of unit step signal input, time step is 10, number of time step is 20, system output without noise C_s and system output with noise level of 5% $C_{s\text{-}n}$ are shown in Table 1.

***Table 1.** System output of Example 1 (without noise and with noise)*

t	**0**	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
C_s	0.00	0.03	0.28	0.77	1.40	2.06	2.66	3.18	3.61	3.95	4.22
C_{s-n}	0.000	0.034	0.290	0.746	1.389	2.107	2.703	3.107	3.635	3.784	4.323
t	**110**	**120**	**130**	**140**	**150**	**160**	**170**	**180**	**190**	**200**	**--**
C_s	4.42	4.57	4.69	4.77	4.83	4.88	4.91	4.94	4.95	4.97	--
C_{s-n}	4.405	4.441	4.517	4.536	4.607	5.120	5.134	4.821	5.019	4.966	--

The parameters setting of PSO are: $c_1 = c_2 = 1.4962$, biggest iteration is 200, initial population number is 40, particle dimension D=4, linear descend inertia weight ranges from 0.9 to 0.4. C_{s-n} as input of the objective function, C_s as the comparison of model G output C_m. Fitting formula is:

$$G(s)=\frac{5.1}{(38.3s+1)(18.6s+1)}e^{-11.1s} \tag{17}$$

Fitting results are shown in Fig. 2, the system output standard deviation is 0.0401, under the consideration of C_s.

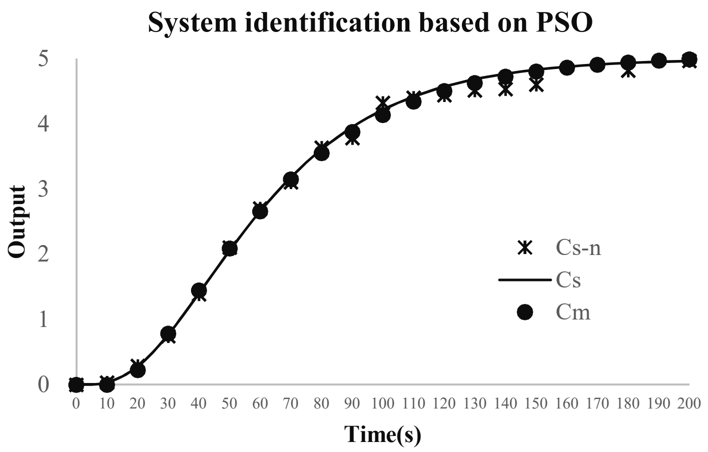

***Fig. 2** Fitting results of Example 1*

Example 2. The system structure is a fourth-order without time delay model:

$$G(s)=\frac{2.4}{(0.6s+1)(2s+1)(7s+1)(20s+1)} \tag{18}$$

Under the conditions of unit step signal input, time step is 5, number of time step is 20, system output without noise C_s and system output with noise level of 5% C_{s-n} are shown in Table 2.

***Table 2.** System output of Example 2 (without noise and with noise)*

t	**0**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
C_s	0.00	0.03	0.28	0.77	1.40	2.06	2.66	3.18	3.61	3.95	4.22

C_{s-n}	0.000	0.034	0.290	0.746	1.389	2.107	2.703	3.107	3.635	3.784	4.323
t	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**--**
C_s	4.42	4.57	4.69	4.77	4.83	4.88	4.91	4.94	4.95	4.97	--
C_{s-n}	4.405	4.441	4.517	4.536	4.607	5.120	5.134	4.821	5.019	4.966	--

The parameters setting of PSO are the same as them in Example 1. C_{s-n} as input of the objective function, C_s as the comparison of model G output C_m. Fitting formula is:

$$G(s)=\frac{2.4}{(14.9s+1)(11.0s+1)}e^{-1.9s} \tag{19}$$

Fitting results are shown in Fig. 3, the system output standard deviation is 0.0094, under the consideration of C_s.

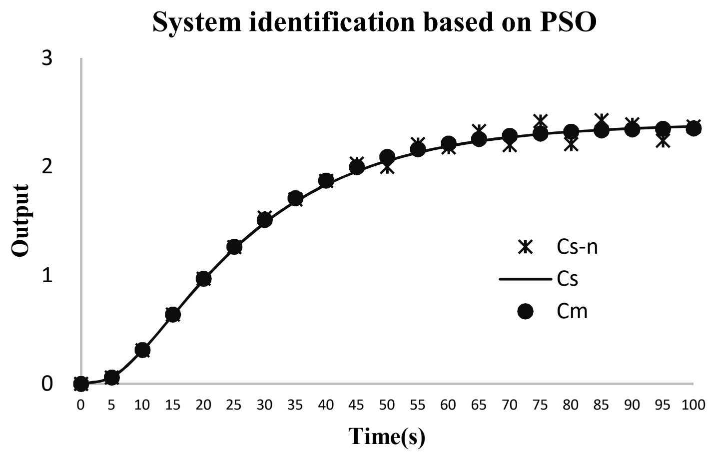

Fig.3 *Fitting results of Example 2*

Simulation results indicate that the method of system identification based on PSO not only has the advantages of simple process, but also high precision and quick calculating speed.

CONCLUSION

System identification is the basis of control theory and state estimation. Identification results have a direct impact on subsequent control results. PSO is a simple and fast algorithm and has been widely used in optimization problems in different fields. In this paper, PSO is applied in the field of system identification of HVAC system. From the simulation results, we can conclude that this method has good adaptability, robustness and application prospect in HVAC system.

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