2005 American Control Conference
June 8-10, 2005. Portland, OR, USA

Modeling Identification of Power Plant Thermal Process Based on PSO Algorithm

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Abstract--**In order to overcome the disadvantages of common model identification methods for thermal process, a novel identification solution based on the Particle Swarm Optimization (PSO) was proposed in this paper. The effectiveness of the proposed identification algorithm is tested by simulation experiments in the common thermal process models. The experiments show excellent results in term of identification accuracy and effectiveness. The PSO approach provides the characteristics of ease realization and high identification accuracy compared with the identification results by improved genetic algorithm.**

I. INTRODUCTION

The thermal process model plays an important role in the design, analysis and verification of control system. So research on system modeling is one of the major concerns in the research of thermal process. In thermal process models, the transfer function in power plant is a useful model which playing an important part in the design, debugging and parameters optimization of control system. The common parameters identification methods of transfer function include the step response method, frequency response method, least squares algorithm, maximum likelihood method, fuzzy modeling method, neuron network and genetic algorithm, etc. Generally, step input or M sequence signal is used in these identification methods, but it is difficult to create these kinds of signal in power plant. Fuzzy modeling method and neural network can be used to estimate the parameters of transfer function in thermal process. But these methods still have some disadvantages. In fuzzy modeling method, many structure parameters should be decided properly. Neural network has no systemic solutions on the decisions of hidden layer's number, the neural cell's number in hidden layer and the initialization of weights. GA method must deal with encoding and decoding operations, so it results in enormous computational efforts. The procedure of parameters identification of transfer function is still cockamamie.

Particle Swarm Optimization (PSO) is a population-based computation technique introduced first by Kennedy and Eberhart in 1995. The underlying motivation for the development of PSO algorithm was social behavior of animals such as bird flocking, fish schooling, and swarm. Some of the attractive features of the PSO include the ease of implementation and the fact that no gradient information is required. It has been widely used to solve an array of different optimization problems. In fact, In fact, system modeling can be converted to an optimization problem. In this work, the PSO algorithm was first used to estimate the parameters of transfer function of thermal process. The comparison of PSO identification results to some typical thermal process with GA (genetic algorithm) showed that the PSO algorithm is more effective for modeling for thermal process with easy implementation.

This paper is organized as follows. Section 2 describes the transfer function model of thermal process. The PSO algorithm for transfer function model parameter estimation is proposed at section 3. The identification results are given at section 4. The conclusions are summary at section 5.

II. DESCRIPTION OF THERMAL PROCESS TRANSFER FUNCTION MODEL

To thermal process, the typical transfer function can be considered as follows

$$G(s)=\frac{y(s)}{u(s)}=\frac{b_m s^m+b_{m-1}s^{m-1}+\ldots+b_1 s+b_0}{a_n s^n+a_{n-1}s^{n-1}+\ldots+a_1 s+a_0} \qquad (1)$$

The object function used to identify transfer function of thermal process can be calculated as

$$f_{itness}=\sum[y(t)-\tilde{y}(t)]^2 \qquad (2)$$

where, y is the output of identification result, $\tilde{y}$ is the output actual process.

This work was supported by the National Science Foundation of China (No.70471052)

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The optimization process is to get the optimal parameters $a_1, a_2, \cdots, a_n$, $b_1, b_2, \cdots, b_m$ which makes f_{itness} minimum. It is shown that by simulation results that the optimization searching is ineffective if the transfer function in (1) used.

One of the main reasons is the value of coefficient in (1) is different widely because of the large time constant and high order. For example, the transfer function of main steam system in a power plant is given as follows

$$G(s) = \frac{9}{(1+15s)^2(1+20)^3} \tag{3}$$

The polynomial for corresponding to (1) is calculated as follows

$$G(s) = \frac{9}{1.8e6s^5 + 5.1es^4 + 5.7e4s^3 + 3225s^2 + 90s + 1} \tag{4}$$

In the polynomial form, a_5 =18000000, a_0 =1,it is difficult to set a reasonable searching area for the parameters. If the area is too small, the optimal point can't be included. If the area is too large, the searching of optimal method will be ineffective.

Another reason is that the value of coefficients may not match. Many kinds of coefficients combination are insignificant, this will reduce the calculation speed. According to the characteristics of thermal process in power plant, their function can be written as following forms:

For the self-balance system:

$$G(s) = \frac{Ke^{-\tau s}}{(1+T_1 s)(1+T_2 s)...(1+T_n s)} \tag{5}$$

For the self-imbalance system:

$$G(s) = \frac{Ke^{-\tau s}}{s(1+T_1 s)(1+T_2 s)...(1+T_n s)} \tag{6}$$

where, the searching area of the coefficients can be set according experiment, T_n =0.01~100, the delay time τ =0~300, K =0.01~100.

In this paper, the PSO algorithm is used to estimate the parameters $\theta = [\tau, a_1, a_2, \cdots, a_n, b_1, b_2, \cdots, b_m]$ shown in (5) or (6). To assure the calculation precision, the object function in this paper given in (7).

$$f_{itness} = \sum_{t=1}^{M} 100[y(t) - \tilde{y}(t)]^2 \tag{7}$$

where, y is the output of identification result, $\tilde{y}$ is the output actual process, M is the number of sample data.

III. DESCRIPTION OF THE PSO ALGORITHM FOR IDENTIFICATION

A. The Particle Swarm Optimization Algorithm

PSO is similar to evolutionary computation techniques in that a population of potential solutions to the optimal problem under consideration is used to probe the search space. Each potential solution is also assigned a randomized velocity, and the potential solutions, called *particles*, correspond to individuals. Each particle in PSO flies in the *D*-dimensional problem space with a velocity dynamically adjusted according to the flying experiences of its individuals and their colleagues. The location of the *i*th particle is represented as $X_i = [x_{i1}, x_{i2}, ..., x_{iD}]$, where $x_{id} \in [l_d, u_d]$, $d \in [1, D]$, l_d, u_d are the lower and upper bounds for the *d*th dimension, respectively. The best previous position (which gives the best fitness value) of the *i*th particle is recorded and represented as $P_i = [p_{i1}, p_{i2}, ..., p_{iD}]$, which is also called P_{best} . The index of the best particle among all the particles in the population is represented by the symbol g . The location P_g is also denoted as g_{best} . The velocity of the *i*th particle is represented as $V_i = [v_{i1}, v_{i2}, ..., v_{iD}]$, and is clamped to a maximum velocity $V_{\max} = [v_{\max 1}, v_{\max 2}, ..., v_{\max D}]$, which is specified by the user. The particle swarm optimization concept consists of, at each time step, regulating the velocity and location of each particle toward its P_{best} and g_{best} locations according to the Eqs. (8a) and (8b), respectively:

$$v_{id}^{n+1} = wv_{id}^n + c_1 r_1^n (p_{id}^n - x_{id}^n) + c_2 r_2^n (p_{gd}^n - x_{id}^n) \tag{8a}$$

$$x_{id}^{n+1} = x_{id}^n + v_{id}^{n+1} \tag{8b}$$

where w is *inertia weigh;* c_1, c_2 are two positive constants, called *cognitive* and *social* parameter respectively; *d*=1,2,…,*D; i*=1,2,…,*m*, and *m* is the size of the swarm; r_1, r_2 are random numbers, uniformly distributed in [0,1]; and *n*=1,2,…,N, denotes the iteration number, N is the maximum allowable iteration number.

B. The Process of Identification Based on the PSO Algorithm

The process for implementing PSO for transfer function model parameter estimation is as follows:

Step 1: Initialize related parameters, including the size of swarm m, the inertia weight w, the acceleration constants c_1 and c_2, the maximum velocity $V_{\max}$, the stop criterion and the initial position and velocity of each particle.

Step 2: Evaluate the desired fitness function values for current each particle.

Step 3: Compare the evaluated fitness value of each particle with its P_{best}. If current value is better than P_{best}, then set the current location as the P_{best} location. Furthermore, if current value is better than g_{best}, then reset g_{best} to the current index in the particle array.

Step 4: Change the velocity and location of the particle according to the Eqs. (8a) and (8b), respectively.

Step 5: Loop to step 2 until a stop criterion is met. The criterion usually is a sufficiently good fitness value or a predefined maximum number of generations $G_{\max}$.

IV. SIMULATION TEST AND RESULTS

To verify the performance of the PSO algorithm identification method, the simulation experiments are conducted and two kinds of thermal process are identified.

A. Example 1: The Thermal Process without Delay

Assume the transfer function of thermal process can be described as follows

$$G(s) = \frac{0.6}{(1+10s)(1+20s)(1+30s)} \tag{9}$$

The coefficients of (9) corresponding to (1) are:
a_3=6000, a_2=1100, a_1=60, a_0=1, K=0.6, τ=0, Q_r=3,
where Q_r is the model order. In simulation tests, the parameters of PSO algorithm are selected as: w=1.2~0.1,which means that w starts from 1.2 and gradually decreases to 0.1; $m = 20$, $c_1 = 0.5, c_2 = 0.5$. The number of estimated model parameters equals four, therefore D is selected as 4.

(1). For a Step Input

In experiments, the simulation time equals 300 seconds and sample time is selected as 1 second. The stop criterion is iterative generations $n > 50$ or object function $f_{itness} \leq 0.19$. The identification results are shown in TAB.I.

TABLE I
PSO IDENTIFICATION RESULTS OF (9) FOR STEP INPUT (Q_r=3)

N	K	T_1	T_2	T_3	f_{itness}	n
1	0.5912	11.4719	22.2463	25.0138	0.0875	18
2	0.5994	9.7135	20.585	29.8494	0.1034	25
3	0.5997	13.8371	13.952	31.8454	0.1195	22
4	0.5946	10.2739	21.3146	27.882	0.1808	19
5	0.6056	9.1308	20.1202	31.538	0.075	25
6	0.6179	7.1477	25.6551	28.9483	0.1832	22
Average	0.6017	10.2645	20.6455	29.1795	0.1249	22

TABLE II
IMPROVED GA IDENTIFICATION RESULTS OF (9) FOR STEP INPUT(Q_r=3)

N	K	T_1	T_2	T_3
1	0.602	9.19	22.7	28.16
2	0.599	10.60	17.2	32.20
3	0.599	13.7	17.7	27.86
4	0.601	9.94	21.7	28.51
5	0.603	8.48	26.0	25.99
Average	0.601	10.32	21.06	28.54

The identification results based on the improved genetic algorithm are given in TAB.II. From the results shown in TAB.II and TAB.I, it is shown that the average iterative generations is less than the one of GA identification method.

To check the sensitivity of the PSO algorithm to the order of model, set the order of model to 2,4,5 (the actual model of

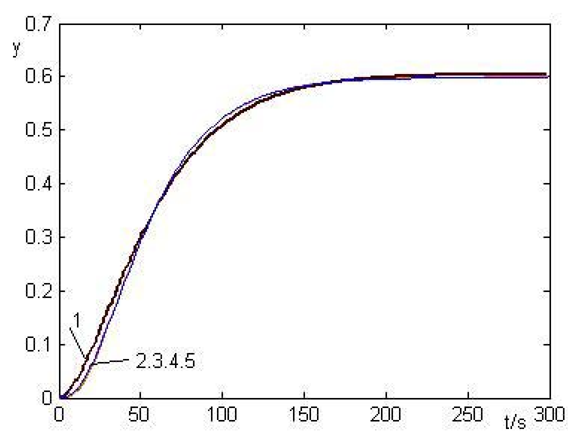

Fig. 1. Step response of (9) and identification results (Q_r=3,4,5)

TABLE III

PSO IDENTIFICATION RESULTS OF (9) FOR STEP INPUT(Q_r =2,4,5)

Q_r	K	T_1	T_2	T_3	T_4	T_5	f_{itness}	n
2	0.6051	30.2992	30.7751	-	-	-	3.3982	15
4	0.6000	3.3365	4.7401	25.1065	26.8875	-	0.1385	26
5	0.5996	1.9526	2.4701	4.0669	23.0670	28.7694	0.3909	23

TABLE IV

IMPROVED GA IDENTIFICATION RESULTS OF (9) FOR STEP INPUT(Q_r =2,4,5)

Q_r	K	T_1	T_2	T_3	T_4	T_5	f_{itness}	n
2	0.604	29.6	31.1	-	-	-	4.58	70
4	0.599	3.85	4.74	24.7	27.4	-	0.09	32
5	0.600	1.56	3.08	4.79	23.9	26.9	0.17	69

TABLE V

PSO IDENTIFICATION RESULTS OF (9) FOR RANDOM OPERATION INPUT

N	K	T_1	T_2	T_3	f_{itness}	n
1	0.5983	9.7797	20.3777	30.4293	0.0862	22
2	0.5948	9.589	23.4373	25.8306	0.0851	14
3	0.6011	10.8847	15.8439	33.1015	0.0931	22
4	0.6053	8.5275	20.9200	31.9133	0.0309	29
5	0.6020	9.6706	22.4598	26.5003	0.1463	14
Average	0.6003	9.6903	20.6077	29.5550	0.0883	20

(10) equals 3), the identification results are given in TAB.III.

The identification results of improved GA method are shown in TAB.IV. It is clearly that the algorithm is not sensitive to the order of model. The corresponding step response curves are shown in Fig. 1, curve 2 is the response of actual process (9), 1,3,4,5 is corresponding to identification model of order taken as 2,3,4,5. It is shown in Fig.1 that the identification results coincide with the response curve of (9).

(2). For a Random Operation Signal Input

The operation signal is simulated by a random signal with amplitude value =-1~1, width=0~50s. Set Q_r =3, the stop criterion is iterative generations $n > 50$ or object function $f_{itness} \le 0.15$. The identification results are shown in TAB.V. The corresponding response curve is shown in Fig.2, where 1 is input signal 2, 2 is output of model (9), 3 is identification result.

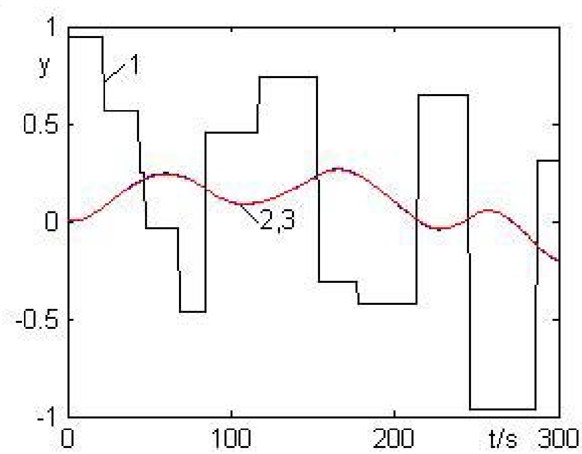

Fig. 2. PSO identification results of (10) for random operating signal input

(3). Step Input with Noise

Assume that there is a noise signal in the step input. The noise is simulated by Matlab random signal. Its amplitude is Aw, frequency is same as calculation step (0.5s). The stop

TABLE VII

PSO IDENTIFICATION RESULTS OF (10) FOR STEP INPUT (Q_r =3)

N	K	T_1	T_2	T_3	f_{itness}	τ	n
1	0.5984	11.5799	14.4054	33.1670	0.1029	61.0706	10
2	0.6061	9.0421	14.8764	35.4217	0.1895	62.1891	24
3	0.6028	12.3664	15.2392	33.1449	0.0341	59.6755	24
4	0.6025	9.5446	18.6813	31.6536	0.1052	60.5937	15
5	0.5976	9.3825	19.0467	28.9882	0.1098	62.2673	28
6	0.6007	9.6518	22.5643	30.1536	0.1032	61.2420	26
Average	0.6014	9.6518	17.4689	32.0882	0.1075	61.1730	21

TABLE VIII

PSO IDENTIFICATION RESULTS OF (10) FOR RANDOM OPERATING INPUT

N	K	T_1	T_2	T_3	f_{itness}	τ	n
1	0.6029	10.9298	21.0528	29.2831	0.0686	59.1789	3
2	0.6083	8.5088	15.6733	34.4652	0.0898	61.8909	18
3	0.6236	11.9737	13.7876	35.7593	0.0608	59.8143	5
4	0.6006	8.9851	18.4995	30.9231	0.1275	60.8699	14
5	0.6035	9.4693	21.5424	29.5687	0.0837	61.5349	23
6	0.6120	10.0122	21.6239	27.4162	0.0961	61.3477	21
Average	0.6085	9.9798	18.6966	31.2359	0.0877	60.7728	14

TABLE VI

PSO IDENTIFICATION RESULTS OF (9) WHEN NOISE EXIST

N	A_m	K	T_1	T_2	T_3	f_{itness}	n
1	0.1	0.6010	9.8341	20.3782	30.0675	0.0735	26
2	0.2	0.5997	8.8698	22.2901	28.7190	0.1229	21
3	0.5	0.6003	10.8753	19.5354	29.5059	0.1339	32
4	1.0	0.5987	11.4878	18.5672	29.5357	0.1170	25
Average	0.45	0.5999	10.2667	20.1927	29.4570	0.1118	26

criterion is iterative generations $n > 50$ or object function $f_{itness} \le 0.15$. The identification results are shown in TAB.VI.

The corresponding response curve is shown in Fig.3 with N=1, where 1 is step input+noise (Aw=0.1), 2 is output of model (10), 3 is the identification result.

It is shown by TAB.VI and Fig.3 that PSO identification results are satisfactory even the noise is strong. This is mainly because the frequency of thermal process model is less than which of noise, so it can filter high frequency signal such as noise. Even if there is a strong noise signal in the input of thermal process, the PSO identification results are satisfactory.

B. *Example 2: The Thermal Process with Delay*

Assume the thermal process model changes from (9) to (10)

$$G(s) = \frac{0.6e^{-60s}}{(1+10s)(1+20s)(1+30s)} \qquad (10)$$

The parameters of PSO algorithm and identification process keep same as the ones in example 1. The

TABLE IX
PSO IDENTIFICATION RESULTS OF (11) WHEN NOISE EXIST

N	A_m	K	T_1	T_2	T_3	f_{itness}	τ	n
1	0.1	0.5998	9.6455	18.6982	30.6115	0.0923	59.9799	28
2	0.2	0.5988	9.3962	19.5145	29.6830	0.1316	61.6243	27
3	0.5	0.5997	8.2486	22.9639	28.1650	0.1104	60.9428	24
4	1.0	0.5994	7.4142	19.5165	31.0838	0.1621	61.7364	24
Average	0.45	0.5994	8.6761	20.1733	29.8858	0.1241	61.0709	26

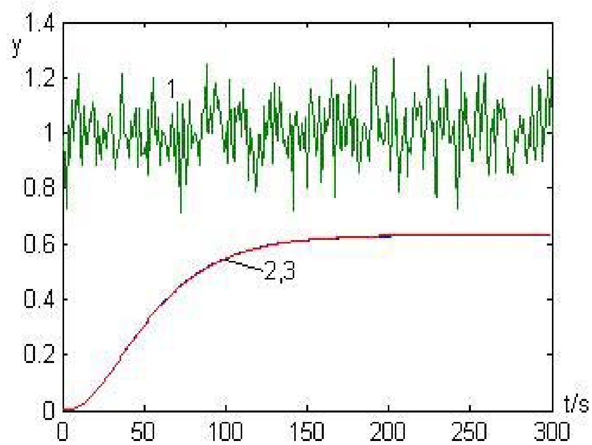

Fig. 3. PSO identification result of (9) when noise exist

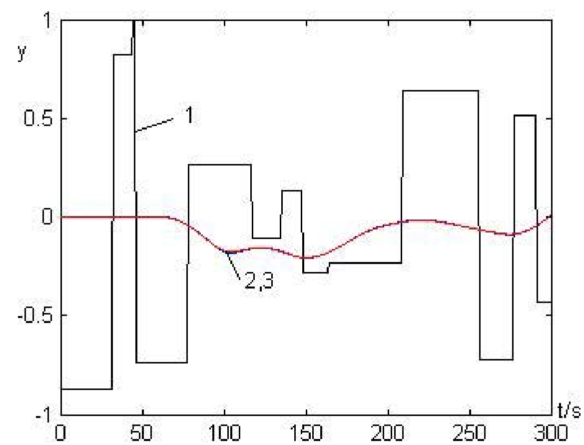

Fig.4. PSO identification results of (10) for random operating signal input

identification results for step input, random operating signal, step input with noise are shown in TAB.VII~TAB.IX.

It is shown by simulation results in TAB.VII~TAB.IX that the PSO identification results are satisfactory for the thermal process with delay, no matter what kinds if input signal is used, even is a strong noise exist in input signal.

V. CONCLUSIONS

The PSO algorithm for thermal process modeling has been presented in this work. No matter what kind of input signal is used, the PSO algorithm can always obtain satisfactory identification results even if a strong noise exists. Compared with the genetic algorithm-based identification method, the PSO algorithm has the following main advantages.

① The PSO algorithm's structure is simple and can be easy implementation.

② The parameters of the PSO algorithm have less influence on the identification results.

③ The searching speed of the PSO algorithm is fast.

The identification results showed that the PSO algorithm is an effective approach to model identification of thermal process. This work indicated that the PSO algorithm is certainly a promising candidate for modeling of thermal process.

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