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RESEARCH ARTICLE

Tong ZHANG, Yahui WANG, Anli YE, Jian WANG, Jianchao ZENG

A new research of identification strategy based on particle swarm optimization and least square

Abstract Within the heat and moisture system that is complex in the air-conditioning rooms of large space building, the existence of delay makes the stability cushion reduced, which thereby makes the estimated parameters more complex. In this paper, particle swarm optimization (PSO) is integrated with least square (LS) to improve least squares (short for PSOLS). LS, optimized by PSO, identifies the heat and moisture system parameters of the existence of delay in the air-conditioning rooms by sampling input and output data. In view of this delay system, the identification is an effective solution to nonlinear system which LS can not identify directly. The simulation results show that PSOLS is quite effective, and its global optimization has great potential.

Keywords least square (LS), particle swarm optimization (PSO), system identification, air-conditioning room

1 Introduction

Heat and moisture transfer in air-conditioning rooms of the buildings plays an important role in air-conditioning load, building energy consumption, and thermal comfort of the living environment. The study on this matter is the foundation of the researches of air-conditioning load calculating method, building energy analysis technology, building energy-saving technologies, and thermal comfort of the living environment. The factors that impact the heat and moisture transfer in air-conditioning rooms are complex. Since only one theoretical modeling method cannot accurately analyze the heat and moisture transfer in different environments, which is quite necessary to control, the adoption of appropriate identification algorithm through experiments can improve it. Experiments and researches are based on the modern theory of heat and moisture transfer of air-conditioning rooms, trying to find the effective ways to improve the measures promote the development on its research and energy-saving technology, speed up China's target of building energy conservation, improve the living environment, and benefit to the sustainable technological progress of building the field. This paper will combine particle swarm optimization (PSO) and least square (LS) into a PSOLS method, which samples input and output data of the online identification of delay in the system.

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Tong ZHANG (✉)
RIOH Transport Consultants Ltd., Research Institute of Highway, Ministry of Transport, Beijing 100088, China
E-mail: zhang_tong@hotmail.com

Tong ZHANG, Yahui WANG, Anli YE
School of Electric and Information Engineering, Beijing University of Civil Engineering and Architecture, Beijing 100044, China

Jian WANG
Department of Technical Conditions, National Institute of Metrology P.R.China, Beijing 100013, China

Jianchao ZENG
Taiyuan University of Science and Technology, Taiyuan 030024, China

2 Selection for control model of heat and moisture system in air-conditioning rooms

As to the heat and moisture system of the air-conditioning room, the input and output of the transfer function can be used approximately with the transfer function of the first-order lag, which is not accurate enough obviously. Therefore, we consider the model with the system transfer function of the second-order lag to improve the accuracy of it. Simultaneously, applying the least squares identification algorithm, the transfer function of the second-order lag is different. The specific process is as follows:

Assume that the transfer function between input variables U and output variables Y is the system of the second-order lag:

$$\frac{Y(s)}{U(s)} = \frac{K_{\mathrm{p}}}{(T_1 s + 1)(T_2 s + 1)} \mathrm{e}^{-\tau s}. \tag{1}$$

In Eq. (1), K_p is the proportional coefficient, T_1 and T_2 are system parameters, and τ is the time-delay parameter.

Carry out identity transformation, the process is described as follows:

$$\frac{A}{T_1s+1}+\frac{B}{T_2s+1}\equiv\frac{A(T_2s+1)+B(T_1s+1)}{(T_1s+1)(T_2s+1)}$$
$$\equiv\frac{K_p}{(T_1s+1)(T_2s+1)}$$
$$\Rightarrow\begin{cases}A=\dfrac{K_pT_1}{T_1-T_2},\\ B=-\dfrac{K_pT_2}{T_1-T_2}.\end{cases}\quad(2)$$

Then, the transfer function can be transformed into

$$\frac{\frac{K_pT_1}{T_1-T_2}\mathrm{e}^{-\tau s}}{T_1s+1}+\frac{-\frac{K_pT_2}{T_1-T_2}\mathrm{e}^{-\tau s}}{T_2s+1}$$
$$=\frac{K_pT_1}{T_1-T_2}\frac{\mathrm{e}^{-\tau s}}{T_1s+1}-\frac{K_pT_2}{T_1-T_2}\frac{\mathrm{e}^{-\tau s}}{T_2s+1}.\quad(3)$$

Assume that the period of data sampling is T, and $nT=\tau$; after Z transform, the transfer function can be transformed into

$$\frac{Y(z)}{U(z)}=\frac{K_p}{T_1-T_2}\frac{z^{-n}}{1-\mathrm{e}^{-T/T_1}z^{-1}}-\frac{K_p}{T_1-T_2}\frac{z^{-n}}{1-\mathrm{e}^{-T/T_2}z^{-1}}.\quad(4)$$

There is

$$Y(z)(T_1-T_2)-Y(z)(T_1-T_2)\left(\mathrm{e}^{-\frac{T}{T_1}}+\mathrm{e}^{-\frac{T}{T_2}}\right)z^{-1}$$
$$+Y(z)(T_1-T_2)\mathrm{e}^{-\left(\frac{T}{T_1}+\frac{T}{T_2}\right)}z^{-2}$$
$$=U(z)K_p\mathrm{e}^{-\frac{T}{T_1}}z^{-(n+1)}-U(z)K_p\mathrm{e}^{-\frac{T}{T_2}}z^{-(n+1)}.\quad(5)$$

In the form of differential equations

$$y(k)=\left(\mathrm{e}^{-\frac{T}{T_1}}+\mathrm{e}^{-\frac{T}{T_2}}\right)y(k-1)-\mathrm{e}^{-\left(\frac{T}{T_1}+\frac{T}{T_2}\right)}y(k-2)$$
$$+\frac{K_p}{T_1-T_2}\left(\mathrm{e}^{-\frac{T}{T_1}}-\mathrm{e}^{-\frac{T}{T_2}}\right)u(k-n-1).\quad(6)$$

The precondition of applying least square is the identified object, which is linear, so the identification objects abide to the superposition principles of linear systems theory. The return air temperature is affected by the supply air temperature, outdoor temperature, and natural source temperature, and these three factors can be linear superposition. Therefore, a temperature system of air-conditioning room can be viewed as a multi-input single-output (MISO) system, which has three inputs and a single output. Each input affects transfer function of output identically, so the influence of three inputs on the output can also be written in their common forms, namely,

$$y(k)=\theta_1y(k-1)+\theta_2y(k-2)+\theta_3u_1(k-\tau_1)$$
$$+\theta_4u_2(k-\tau_2)+\theta_5u_3(k-\tau_3).\quad(7)$$

In Eq. (7), y is the return air temperature; u_1 is the outdoor temperature; u_2 is the supply air temperature; u_3 is natural source temperature; θ_i, $i=1,2,3,4,5$, are the system parameters that are to be identified; and τ_i, $i=1,2,3$, are the lag time that are to be identified (in the form of the multiplier of sampling period). They are all the parameters to be estimated [1–3].

3 PSOLS

3.1 Particle swarm optimization (PSO) [4–6]

3.1.1 PSO sources

PSO is a kind of evolution technology developed by J. Kennedy and R. C. Eberhart in 1995, which came from a simplified model of social simulation. The “swarm” of the PSO accord with five basic principles of colony intelligence proposed by M. M. Millonas in developing the model of artificial life. “Particle” is a concessive choice, because all group members need to be described as no quality, no size, and their speed and acceleration state need to be described.

3.1.2 Basic principle

Assuming that in a D-dimensional search space, there are n particles composing a particle swarm. In addition, the position of the ith particle is $X_i=(x_{i1},x_{i2},\ldots,x_{iD})$, $i=1,2,\ldots,n$, which is a potential solution to the optimization. By substituting it into the objective function, we can calculate the corresponding fitness value, and the pros and cons of value can be measured. The current flight speed of the ith particle in the search space is $V_i=(v_{i1},v_{i2},\ldots,v_{iD})$; the optimal position experienced by the ith particle is $P_i=(p_{i1},p_{i2},\ldots,p_{iD})$, namely, the optimal position of individual history, recorded as P_{Best}; the optimal position experienced by all particles is $P_g=(p_{g1},p_{g2},\ldots,p_{gD})$, namely optimal position of overall history, recorded as G_{Best}. For the particles of each generation, the evolution equation of G_{Best} model is as follows:

$$v_{i+1}=v_i+c_1\times r_1\times(p_i-x_i)+c_2\times r_2\times(p_g-x_i),\quad(8)$$

$$x_{i+1}=x_i+v_{i+1}.\quad(9)$$

In Eq. (8), both c_1 and c_2 are the normal numbers, namely the acceleration factors, the appropriate acceleration factor is propitious for the rapid convergence algorithm and the detachment of the local extreme value; r_1 and r_2 are two random numbers changing within [0,1], and they ensure the diversity and random search of the particle swarm. On the right side of Eq. (8), the first part is the previous speed of the particles, and it enables the particles have expanding trend in the search space so that the algorithm has global search capability; the second part is cognitive portion, showing the progress that the particles draw their own experience knowledge; the third part is the social portion, showing the progress that the particles learn experience knowledge of other particles and incarnating information sharing and collaboration community in each particle.

3.2 Least square (LS)

LS is a method of the parameter, which is the square sum to be minimal of the different values ($e(k)$) between the actual observed value (y) and the model calculation value. If obtaining data from the experiments, such as $\{u_1(i),u_2(i),...,u_n(i);y(i)\}, i=1,2,\ldots,N$, the square sum of error is

$$J(a_0,a_1,...,a_n) = \sum_{k=1}^{N} e^2(k) = \sum_{k=1}^{N} [y(k)-a_0-a_1u_1(k)-\cdots-a_nu_n(k)]^2. \tag{10}$$

The key of the estimation for system parameters is to calculate the minimal value of $J(\hat{a}_0,\hat{a}_1,...,\hat{a}_n)$, and $J(\hat{a}_0,\hat{a}_1,...,\hat{a}_n)$ is estimated value of the parameters. Wherever $\{\hat{a}_i\}$ is the least square estimation of $\{a_i\}$, J is a quadratic function of $a_0,a_1,\ldots,a_n$. Therefore, the method of finding extreme value with multivariate functions is feasible.

3.3 Use of PSOLS

Combine PSO with LS and optimize LS by using PSO.

Based on Eq. (8), the G_{Best} model of PSO is improved by using general inertia weight, and the speed evolution equation is

$$v_{i+1} = w \times v_i + c_1 \times r_1 \times (p_i - x_i) + c_2 \times r_2 \times (p_{\mathrm{g}} - x_i), \tag{11}$$

$$w = (x_{\max} - x_{\min})(t_{\max} - t_{\min}) + x_{\min}. \tag{12}$$

In Eq. (11), w is inertia weight, which enables particles to maintain movement inertia. Moreover, w can be calculated by using Eq. (12) [5,6].

When the G_{Best} model of PSO is a local optimal point, the algorithm will be limited to local optimal point, and premature convergence phenomenon appears. The multi-function is limited to local optimal point more easily. Therefore, the best neighborhood position is introduced, which is L_{Best}, and the best neighborhood position of particle i is $L_i = (l_{i1},l_{i2},...,l_{iD})$ [7–9]. The speed evolution equation of PSO L_{Best} model is

$$v_{i+1} = w \times v_i + c_1 \times r_1 \times (p_i - x_i) + c_2 \times r_2 \times (l_i - x_i). \tag{13}$$

L_{Best} model has a strong global search capability. The existence of a number of neighborhoods will hold the optimal number of possible optimal seeds, which can greatly avoid the possibility of local optimum. However, the convergence speed is slow. A good search strategy should have a stronger global search capability in the initial search stage and find the best seeds as many as possible, while in the latter part of the search stage, it should have a stronger local search capability, improving the convergence rate and accuracy. Thus, combining the model of L_{Best} with G_{Best} and combining Eqs. (8), (9), (11), and (13), the speed update equation of PSO is

$$v_{i+1} = w \times v_i + c_1 \times r_1 \times (p_i - x_i) + r_2 \times (c_2 \times (l_i - x_i) + c_3 \times (p_{\mathrm{g}} - x_i)). \tag{14}$$

In Eq. (14), $c_1=2$, $c_2 + c_3=2$. With progressing of the evolution, c_2 decreases, while c_3 increases. Therefore, there are many design means, which may be a linear change or a nonlinear change. The equation of the form of linear changes is as follows:

$$c_2 = 2 \times \frac{\max - \mathrm{iter}}{\max}, \tag{15}$$

$$c_3 = 2 \times \frac{\mathrm{iter}}{\max}. \tag{16}$$

In Eqs. (15) and (16), max is the largest number of iteration, and iter is the current number of iteration.

For the three-input single-output system in Eq. (7), the algorithm flow is written as follows:

Step 1 Initialize the process, speed, position, P_{Best}, L_{Best}, and G_{Best} of each particle in the particle swarm (assume that the number of the swarm is n; the dimension of the space is D, which is also a parameter to be estimated). Moreover, the initialization equation of speed and location are

$$V_{ij} = \mathrm{rand}[0,1] \times (V_j^{\mathrm{u}} - V_j^{\mathrm{l}})V_j^{\mathrm{l}}, \tag{17}$$

$$X_{ij} = \mathrm{rand}[0,1] \times (X_j^{\mathrm{u}} - X_j^{\mathrm{l}})X_j^{\mathrm{l}}. \tag{18}$$

In Eqs. (17) and (18), $i = 1,2,\ldots,n$, $j = 1,2,\ldots,D$, the speed upper limit of the jth dimension is V_j^{u}, the lower limit is V_j^{l}, the variable upper limit of the jth dimension is X_j^{u}, and the lower limit is X_j^{l}.

Step 2 Set the size of the neighborhood in the swarm and divide the neighborhood according to the random serial number of the particles.

Step 3 Calculate the fitness value of each particle. In order to observe and analyze conveniently, the value will be limited within the scope of [0,1]. The fitness function is

$$f(k) = \frac{1}{\sqrt{\sum_{i=1}^{N} (y(k)-y_i(k))^2 + 1}}. \tag{19}$$

Step 4 For each particle, compare its fitness value with optimal position of individual history (P_{Best}). If the current fitness value is optimum, use the current fitness value replace P_{Best}; otherwise, P_{Best} remains unchanged.

Step 5 For each particle, compare its fitness value with the best position (L_{Best}) in the neighborhood. If the current fitness value is optimum, use the current fitness value replace L_{Best}; otherwise, L_{Best} remains unchanged.

Step 6 For each particle, compare its fitness value with the optimal position of overall history (G_{Best}). If the current fitness value is optimum, use the current fitness value replace G_{Best}; otherwise, G_{Best} remains unchanged.

Step 7 Update the speed of each particle according to Eqs. (14)–(16). Determine whether the speed of particles exceeds the maximum speed, such as beyond the maximum speed.

Step 8 Update the position of each particle according to Eq. (9). Return to Step 3 if it fails to reach the end of the given conditions or the largest number of iteration.

4 Identification result and test

In this paper, condition data of the 4th Hall Art Gallery in the winter are adopted. The supply air temperature, outdoor temperature, and natural source temperature are viewed as the input, and the return air temperature of the air-conditioning room as the output. In January 20–27, 2006, the air-conditioning data of eight days, which are sampled every 15 minutes, are viewed as the input and output. Because the business time of Museum of Fine Arts during the day is from 9:00 to 17:00 and, at night, there always has not the air-conditioned circumstances, the recorded data from 9:00 to 17:00 are viewed as the air-conditioning data.

Equation (19) is the fitness function, in this example:

$$\begin{aligned} y_i(k) &= \theta_1 y_i(k-1) + \theta_2 y_i(k-2) + \theta_3 u_{i1}(k-\tau_1) \\ &\quad + \theta_4 u_{i2}(k-\tau_2) + \theta_5 u_{i3}(k-\tau_3). \end{aligned} \tag{20}$$

In the optimization problems of this paper, (θ_1,θ_2,θ_3,θ_4, θ_5,τ_1,τ_2,τ_3) is the position of particles. As parameters are being estimated encode the real number form, the lag coefficient must be rounded before taken into calculation. The scale of PSO is 50; the scale of the neighborhood is 5; parameters c_1= 2, c_2 and c_3 are calculated by Eqs. (15) and (16); and the weight w changes linearly in iteration number from 0.9 to 0.4, namely,

$$w = 0.9 - \frac{(0.9-0.4)\text{iter}}{\max}. \tag{21}$$

For the model, assume that the largest iteration number is 500. The results are shown in Table 1.

Through the analysis of SPSS v 13.0, the correlation of the output data of the model and actual output data, as well as their significance are shown in Table 2.

From the above results analysis, we can see that correlation coefficient with output of model data and the data of the actual sampling is up to 0.966, and the significant level is 0.001. It is very perfect.

5 Conclusions

According to characteristics of global optimal model and the local optimal model of PSO, combining their advantages, the LS has been improved and optimized. The system identification method PSOLS has a high global search capability, a quick convergence, and a high

Table 1 Parameter identification results

parameter	θ_1	θ_2	θ_3	θ_4	θ_5	τ_1	τ_2	τ_3
identification result	0.8363	0.0938	0.0027	0.0545	−0.0065	1	6	3

Table 2 Correlation coefficient

correlation analysis		output data of the model	actual output data
output data of the model	pearson correlation coefficient	1	0.966
	significance level two sided test	–	0.001
	efficacy rates	118	118
actual output data	pearson correlation coefficient	0.966	1
	significance level two sided test	0.001	–
	efficacy rates	118	118

precision. Online parameter identification results obtained from the air-conditioning room of a Museum of Fine Arts shows that by optimizing the model parameters with PSOLS method, the result of identification is very good and efficient. The proposed method, which has a high global search capability, a quick convergence and a high precision, is very effective in nonlinear model for the online identification and parameter estimation.

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