Sensors & Transducers, Vol. 163 , Issue 1, January 2014, pp. 1-8

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Sensors & Transducers
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Model Optimization Identification Method Based on Closed-loop Operation Data and Process Characteristics Parameters

[1] Zhiqiang GENG, [1] Runxue LI, [2] Xiangbai GU
[1] College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029 China.
[2] Sinopec Engineering, Beijing 100029, China
[2] Tel: +86-10-69166327, fax: +86-10-69196645
E-mail: guxb@sinopec.com

Received: 9 October 2013 /Accepted: 9 January 2014 /Published: 31 January 2014

Abstract: Output noise is strongly related to input in closed-loop control system, which makes model identification of closed-loop difficult, even unidentified in practice. The forward channel model is chosen to isolate disturbance from the output noise to input, and identified by optimization the dynamic characteristics of the process based on closed-loop operation data. The characteristics parameters of the process, such as dead time and time constant, are calculated and estimated based on the PI/PID controller parameters and closed-loop process input/output data. And those characteristics parameters are adopted to define the search space of the optimization identification algorithm. PSO-SQP optimization algorithm is applied to integrate the global search ability of PSO with the local search ability of SQP to identify the model parameters of forward channel. The validity of proposed method has been verified by the simulation. The practicability is checked with the PI/PID controller parameter turning based on identified forward channel model.
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Keywords: Model optimization identification, Closed-loop operation data, Process characteristics parameters, PSO, SQP, PID tuning.

1. Introduction

System identification is one of the methods and theories for modeling, which bases on extracting the process information from the data of input and output. For most of industry processes, the system is a part of the feedback system, and which is not allowed to be cut off under the consideration of the economic and security. The closed-loop identification is therefore necessary. The traditional methods of system identification are used for open-loop systems, on the one hand, the same output will be obtained even with the different inputs, so the less information will be got from the process. On the other hand, the noise in the output is closely related with the input through feedback, all of these make the estimation error larger with traditional estimation method and the system unidentified.

Many effective methods are developed for system parameter estimation of the close-loop system [1-6], and can be divided into three categories:

- The indirect identification (ID): Ignore the feedback and identify the open-loop system using measurements of the input and output.

- The direct identification (DI): identify some closed-loop transfer function and determine the open-loop parameters using the knowledge of the controller.
- The joint process identification (JPI): Regard the input and output jointly as the output from a system driven by some extra inputs or set-point signal and noise. Use some methods to determine the open-loop parameters from an estimate of this augmented system.

Regarding ID and JPI, the parameter for the feedback controller must be known before the system test, and one of the measurable signals must be included. This makes the methods limited in real industrial application. The DI method regards the closed-loop system as an open one. While this is not useful for closed-loop system as discussed above. Many methods [7-10] are used to optimize the system parameters in D. I. Pan [4] developed a method to identify the system using NLJ based on a simplex method. The ID method is divided into two steps: first, generating good estimation of the loop sensitive based on extensive closed-loop data, and then the loop sensitivities are used to factor the plant dynamics by inverse filtering. Many methods had been proposed for multivariable system with these approaches, which have some attractive prospects, the inverse filtering step could be daunting for relatively larger multivariable systems. Nikhil [11] developed an approach named trust region SQP to optimize parameters, which will get better result if the good initial point is given. In addition, Jin [3] identified the parameters of model with particle swarm optimization (PSO) algorithm.

NLJ and other methods of DI search the best system parameters without the information of gradient, which made low speed in optimization process. SQP takes advantage of the information, but is sensitive to the initial points. PSO works as an intelligence inspired method that can get better results in search space, however, it is not a good idea to let the swarm search in the whole space. Empirical literature review shows that most researches define the search space subjectively based on their experience, rather than extracting process information from the input and output data of the process industry.

In this paper, we simulated the dynamic characteristic of the process object with the forward channel, so the identification of the process itself transfers to identify the parameters of forward channel model. We take full advantage of the process input and output data and the PI/PID controller parameters to determine the search space of the forward channel's parameters. At the meantime, a composited search method combines PSO with SQP is adopted, which further makes full use of the global search ability of PSO and local search ability of the SQP.

2. Process Object Model Based on Forward Channel

In the context of most practical industrial objects, they can be approximated by applying Second Order System Plus Delay (SOSPD) model or First Order System Plus Time Delay (FOSPD) [3]. Take SOSPD model as example, the model transfer function is given by:

$$G(s) = \frac{Ke^{-\tau s}}{(T_1 s+1)(T_2 s+1)}, \quad (1)$$

The time delay can be replaced by first-order or second-order Pade approximation [4]. This paper uses forward channel to simulate the dynamic characteristics of the system, ensuring output noise and input are independent to get the dynamic characteristics of system. As shown in Fig. 1, the model block diagram shows that in the whole process of identification, system identification can be conducted as long as we capture the output of the controller as well as the actual output of the system, and this will not bring up any interference to the original system, and guarantee the safety of the actual industrial operation.

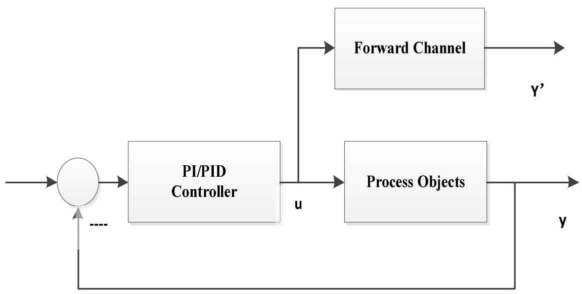

Fig. 1. Identification model based on forward channel.

3. Process Object's Information Extraction Based on Closed-loop Data

3.1. Time Delay Estimation Based on Closed-loop Data

Since the delay time constant is an important process variable parameter, the determination of its value is of great significance to the accuracy of identification. As shown in Eq. 2, the cross correlation function between output u of controller and output y of system is used to solve delay time τ [12].

$$\tau = \max_{\delta} \mathrm{E}[\mathrm{y(i)u(i-}\delta)] = \max_{\delta} \sum_{i=\tau}^{n} u(i\text{-}\delta)\, y(i), \quad (2)$$

When selects suitable $\delta=\tau$, the value of the cross correlation function will be maximized, therefore the estimation value of delay time can be obtained.

3.2. Estimation of Stable Closed-loop PI/PID System's Process Parameters

For the stable closed-loop system with PI/PID controller, the traditional optimization tuning rules will be applied. With the quantitative relationship among the time constant of process object, proportional gain K_c of controller, integration time Ti, and differential time Td, reverse calculation can be used to obtain the time constant of process system object and the estimation of proportional gain. This paper uses Minimum IAE-Shinskey (1996) – page-48 and Minimum IAE-Shinskey (1996) – page-119 [13] to conduct reverse calculation for PI and PID controller relatively, obtaining time constant of process object and process proportional estimated value. The equations are shown in Eq. 3 and Eq. 4.

For PI Controller:

$$\begin{cases} T_1=\dfrac{2*T_i}{2.29*3.5} \\ T_2=\dfrac{1}{2}*T_1 \\ K=\dfrac{0.80T_1}{0.2*T_1*K_c} \end{cases}, \tag{3}$$

For PID Controller:

$$\begin{cases} T_1=2.5*T_d \\ T_2=\dfrac{1}{2}*T_1 \\ K=\dfrac{2.00T_1}{T_d*K_c} \end{cases}, \tag{4}$$

where T_1 and T_2 refer to the time constant, K refers to the process gain in Eq.1, Ti refers to integration time, Td refers to differential time, and *Kc* refers to the gain of controller.

4. The Identification Method for Forward Channel Model Based on Closed-loop Process Information Constraints

4.1. PSO-SQP Algorithm

PSO was developed by Kennedy in 1995 [14]. It is used in electric, energy and optimization [15-17]; Similar to other swarm intelligence optimization algorithms, such as genetic algorithm, each particle represents a possible solution, and has two characteristic parameters including position and velocity. Usually the function value of its position refers to the particle's fitness value, and it is used to evaluate quality of the current particle position. The PSO algorithm first randomly initializes a group of particles in the search space, and then updates the position and velocity according to the optimal positions of both individuals and entire populations based on Eq. 5 and Eq. 6, until the satisfactory solutions are found or the maximize iteration number of optimization has been reached.

$$V_i = w*V_i + C_1*rand()*(pbest_i - x_i) + C_2*rand()*(gbest - x_i) \tag{5}$$

$$x_i = x_i + V_i \ , \tag{6}$$

where $V_i=[V_i^1, V_i^2......V_i^D]$ refers to the velocity of particle *i*, and represents the next direction and step length; $X_i=[X_i^1, X_i^2......X_i^D]$ refers to the current position of particle *i*, $pbest_i$ and *gbest* represent the found optimal positions of individual particles and entire populations relatively. *w* means weight, it is mainly used to carry out the tradeoffs between global and local optimization capacities. C_1 and C_2 refer to accelerating factors, and they relatively represent the changes of local and global approximation rate. *rand()* refers to the random value among [0,1].

Sequential Quadratic Programming (SQP) method is a local optimization method, proposed by Wilson in 1963 [13, 18]. It converts the original problems into QP sub-problems, particularly suitable for nonlinear programming problem.

This paper uses PSO to conduct global optimization. When the global optimal convergence threshold is less than a certain threshold, SQP will be used for local optimization within global optimum. The algorithm description is shown as follow:

1. Initialize the velocity and position of particles, and calculate each particle's individual optimum and the global optimum of whole swarm.
2. Updating velocity and position with regard to Eq. 2 and Eq. 3, as well as updating on particles' individual optimum and global optimum of the swarm.
3. Determine whether the convergence threshold of particles' global optimum is less than a certain set value. If yes, conduct SQP for local exploration by setting the global optimum as the initial point, and initial optimization range as boundary. Otherwise, go to step 2.
4. Determine whether the termination condition of optimization has been reached. If yes, then terminate. Otherwise, go to step 2.

4.2. Fitness Function

As it requires forward channel to obtain the dynamic characteristics of system while conducting system identification, function $f(x)=\int t|y-y'|dt$ is therefore selected as the objective function. During the beginning stage, as Pade performs as delay approximation, the deviation of system identification is large, but *t* is relatively small. However, in the late process, the approximation deviation is getting smaller, and *t* instead, is getting larger. Therefore, it is good to conduct identification on forward channel, so as to obtain the dynamic characteristics of system. In addition, function $f(x)=\int |y-y_{sp}|dt$ plays as fitness function while tuning the system, this further helps ensure small discrepancy of system. Additionally, in actual industrial practical, the decay ratio of system output is usually controlled at a certain ratio between 4:1 to 10:1, thereby this constraint is added in when tuning the system.

4.2.1. Constraint Conditions Formation of Forward Channel Model Optimization Identification Based on Process Information

In order to make the obtained forward channel model to match actual process object, it is necessary to get the estimate values of the forward channel through extracting the process information from closed-loop data, and then appropriately expand them to form an effective optimization search space. Therefore constraint (7) is used to get search space though expanding the extracted process parameters, and set them as the optimization search range for the forward channel model parameters to be identified.

$$1/a*X_{i\_estimate} \le x_i \le a*X_{i\_estimate}, \qquad (7)$$

For the actual industrial applications, the proportional gain K_c of controller and K of process object are usually required to satisfy the constraint of $0 \le K_c*K \le 3.5$ [16]. With combination of the above two proportional gain of the process object, constraint (8) is therefore used to confirm the optimization range of controller proportional gain *K*.

$$[\max(0,1/a*K_{c\_estimate}),\min(3.5/K,a*K_{c\_estimate})] \qquad (1)$$

4.2.2. The Optimization Parameters of PSO

The weight *w* of PSO plays the roles of balancing the particle's local and global search capabilities. When the weight is large, the population has strong global optimization ability. Similarly, the particle swarm performs strong local search ability while the weight is small. Learning factors C_1, C_2 represent the learning ability of particles from individual optimum and global optimum respectively. It has a great impact on the effect of optimization. The linear decrease weight is adopted in this paper, where the parameter in this paper uses $w_{max}=0.9$, $w_{min}=0.4$, and $C_1=C_2=2$.

4.2.3. Data Length

To ensure the data used in closed-loop identification fully represents the actual process object's dynamic characteristics, the selection of appropriate data length is of great importance [5, 19]. Regarding engineering experience, the selection of data length can be considered to use the formulation $N > \frac{150\tau}{T_s}$ or $N > \frac{50T_i}{T_s}$. Based on the above two options, this paper uses $N=\max(\frac{150\tau}{T_s},\frac{50T_i}{T_s})$ to decide data length.

4.2.3. The Optimization and Identification Method Using Forward Channel Model Based on Closed-loop Process Information Constraints

In order to improve the versatility of forward channel closed-loop model identification method based on forward channel, the SOSPD model is selected as the model to be identified. Easily to find that, through the stable closed-loop process information that based on PI/PID control, combined with Eq. 2 ~ 4, the estimation of time constant T_1 and T_2, gain K and delay time constant τ, of the forward channel model can be easily obtained. By further using constraint (7) and (8), the optimization range of the forward channel can also be decided. Next, comprehensively integrate the PSO's global optimization ability with SQP's local search capability, and conduct parameter identification on forward channel model, so as to obtain process object's dynamic characteristics. The flow chart is shown in Fig 2.

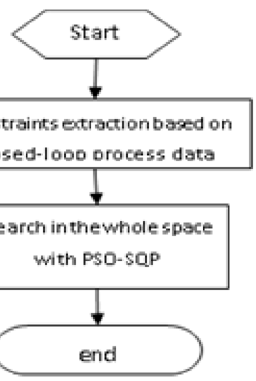

Fig. 2. The identification methods for forward channel model optimization based on closed-loop process information constraints.

5. Simulation

5.1. The Validity of Methods

In order to test and verify the validity of the proposed method, the following process object is selected:

$$G(s)=\frac{e^{-16s}}{(20s+1)(4s+1)}$$

By using PI controller and its transfer function is given as follows:

$$G_c(s)=K_c(1+\frac{1}{T_i s})$$

Conducting simulation research with the proposed method.

5.1.1. Estimation of Process Object's Time Delay

While conducting the identification of system dynamic characteristics, select Kc=1.1286, Ti=30.1968 as [13]. Similarly, when deciding the delay time, set sampling interval Ts=0.2 s, and select the sampled data with t= 0 to 200 Ts. Regarding δ within 0 to 400 Ts. The variation curve of $\sum_{i=\tau}^{n} u(i\text{-}\delta)y(i)$ is shown in Fig. 3, where δ at the peak equals 57 Ts, that is 11.4 s, therefore the estimation of delay time τ_estimate equals 11.4 s.

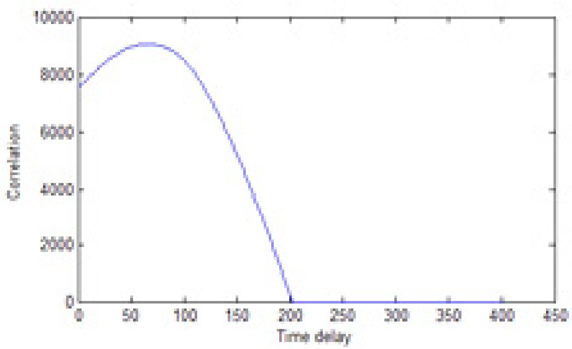

Fig. 3. Correlation coefficient regarding time delay.

5.1.2. Acquisition of Process Object Parameters

Regarding the acquisition of process object parameter, we use known controller parameters and Eq. 3 to conduct reverse solutions, thus we got the estimation value T_1_estimate=18.8377, T_2_estimate=9.4188, K_estimate=3.5442. We can also further obtain the solution range of process object parameters, which can be used as the PSO-SQP optimization range as well.

5.1.3. Optimization Identification for Forward Channel

Regarding the extracted process object parameter, we use constraint (7) and constraint (8) to obtain the following optimization constraints:

$$3.76754 \le T_1 \le 94.1885$$
$$1.88376 \le T_2 \le 47.0940$$
$$0.70884 \le K \le 17.7210$$
$$5.70000 \le \tau \le 22.80000$$

Regarding delay, it can use first-order or second-order Pade approximation. With proposed closed-loop identification method based on forward channel, we can get forward channel model. Here the time delay is approximated by first-order Pade approximate:

$$G(s)=\frac{1}{(18.467s+1)(3.933s+1)} * \frac{1-9.417s}{1+9.417s}$$

In order to verify the validity of the model, the output correlation curve of real object model and forward channel model is shown in Fig. 4, which shows that the forward channel obtained by proposed closed-loop identification method can stimulate the dynamic characteristics of real process object.

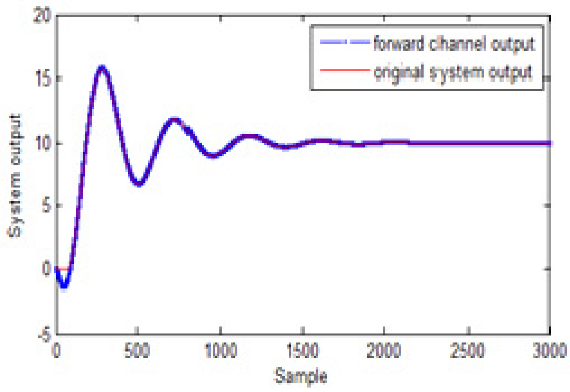

Fig. 4. Comparison for forward channel and original system output.

5.2. The Applicability of Forward Channel Identification Model

In order to further verify the validity of the identified forward channel, we consider using PI/PID parameter tuning to verify the identified forward channel's applicability.

5.2.1. Tuning Model Based on Forward Channel

The block diagram of the closed tuning model based on forward channel model is shown in Fig. 5.

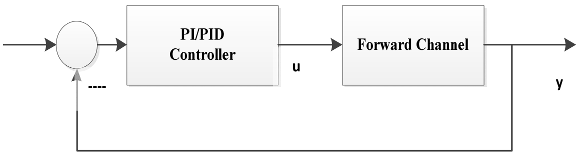

Fig. 5. PI/PID controller's parameter tuning model based on forward channel.

5.2.2. Optimization Tuning of PI/PID Parameters

Through identification, the parameters of forward channel can be obtained. With Eq. 3 and Eq.4, we can get the estimation value of controller's parameters. Then, we use constraint (7) and (8) to obtain the value range of controller's parameters and further use PSO-SQP algorithm to get the PI/PID controller's tuning parameters based on forward channel.

The system output correlation curve of forward channel before and after PI controller's parameters tuning is shown in Fig. 6. And Fig. 7 shows the real process output correlation curve with PI controller parameters original and optimal result obtained from tuning based on forward channel model. The controller's parameters and system performance index before and after optimization tuning is shown in Table 1 and Table 2 respectively, the original parameters is set as [13], which can be regard as experience value. Regarding Fig. 7 and Table 2, the system output curve after forward channel tuning, shows better compared with original controller's control performance.

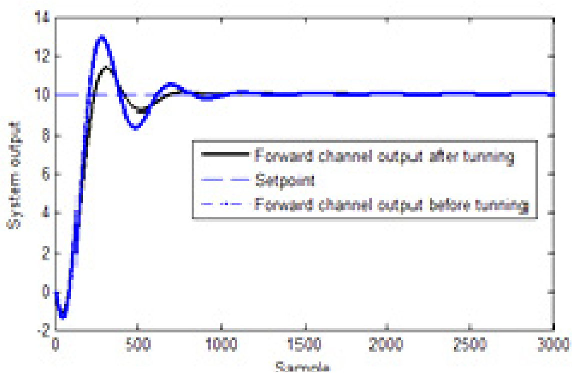

Fig. 6. Correlation curve of forward channel before and after tuning.

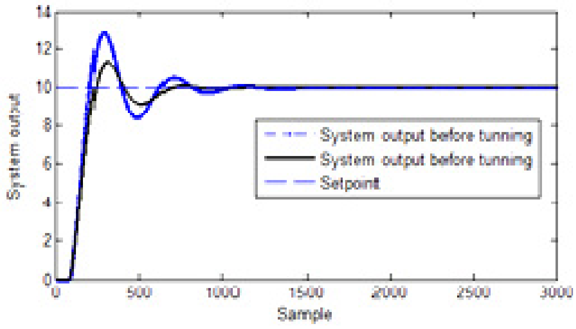

Fig. 7. Correlation curve of original system before and after tuning.

Table 1. Comparison PI parameters of before and after tuning.

Controller Parameters	Original Controller's Parameter	Controller's Parameter of after Tuning
Proportional Gain P	1.1286	0.9276
Integration Time T_i	30.1968	29.9850

Table 2. Comparison of PI controller's performance index.

Performance Index	Original	After Tuning
Overshoot/%	27.97	12.6810
Rise Time/s	41.2	47.8
Adjustment Time/s	192.2	130.2

From above, we have already verified the proposed method's validity and applicability on closed-loop stable loop involved with PI controller. We need further verify the method's applicability on closed-loop stable system with PID controller. While using PID controller, its transfer function is:

$$G_c(s)=K_c(1+\frac{1}{T_i s})(\frac{1+T_d s}{1+\frac{T_d s}{N}})$$

Fig. 8 shows the system output curve of before and after tuning, and Table 3 displays the comparison of control performance index. Through Fig. 8 and Table 3, we can see that the control effect of both system identification and tuning method based on forward channel has been improved compared with original controller's parameters.

Table 3. Comparison of PID controller's performance index.

Performance Index	Original System	After Tuning System
Overshoot/%	51.90	19.89
Rise Time/s	28.2	32
Adjustment Time/s	212.6	135.2

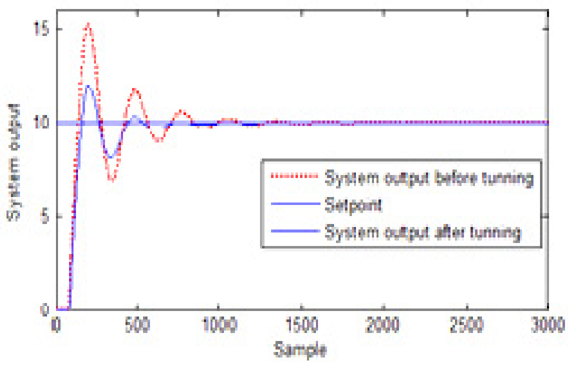

Fig. 8. Correlation Curve of original system before and after PID parameter optimization tuning.

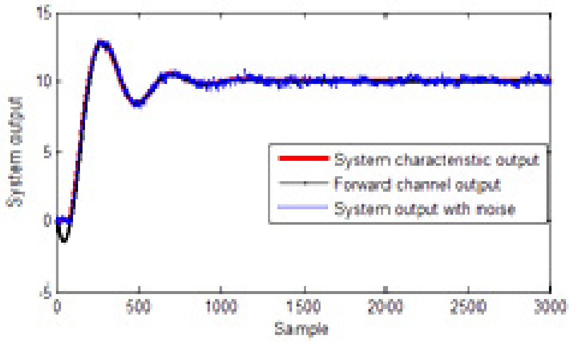

Fig. 9. Comparison for forward channel and original system output.

5.3. The Anti-Jamming of Identification Method

At the process object output, we add in colored noise of 5 %-10 % to steady-state value, and use the proposed identification method and the tuning method above to verify the validity and availability of the identification method. Fig. 9 shows the comparison of system identification output and original system actual output, as well as their characteristics outputs considering the noises added in. Fig. 10 shows the comparison of system characteristics' output though adopting the controller parameter after tuning based on forward channel model and that of the original controller's parameters. From Fig. 9 and Fig. 10, it can be seen that the proposed identification method has a certain anti-jamming capability.

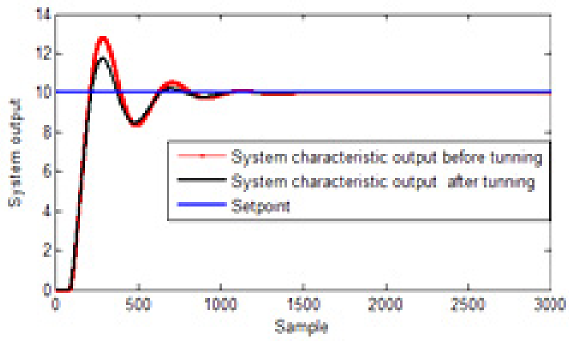

Fig. 10. Characteristic curve of before and after original system tuning.

6. Conclusion

The proposed forward channel optimization identification method is based on closed-loop operation data. The process characteristics information constraints are estimated easily from closed-loop process data and closed-loop stable PI/PID controller parameters. And the optimization search space of the relative parameters in the forward channel is skillfully defined by estimated process characteristics information. It therefore effectively helps understand the optimization process of global traversal and local search. The obtained forward channel is better to fit with the dynamic characteristics of closed-loop system. The simulation research shows the effectiveness of this proposed method, and PI/PID controller tuning results by using the identified forward channel model is quite well. It verifies the applicability of the proposed closed-loop model optimization identification method.

Regarding the industry process, for a large number of applications of PI/PID control loop, it can help ensure the process system safety, and has a wide range of industrial practical application prospects.

Acknowledgements

The work is supported by National natural science foundation of China (61374166), the HI-Tech Research and Development Program of P. R. China (2007AA04Z170) and The Natural Science Foundation of Ningbo (2012A610001).

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