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Fault Diagnosis of Nonlinear Systems Based on Hybrid PSOSA Optimization Algorithm

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Abstract: Fault diagnosis of nonlinear systems is of great importance in theory and practice, and the parameter estimation method is an effective strategy. Based on the framework of moving horizon estimation, fault parameters are identified by a proposed intelligent optimization algorithm called PSOSA, which could avoid premature convergence of standard particle swarm optimization (PSO) by introducing the probabilistic jumping property of simulated annealing (SA). Simulations on a three-tank system show the effectiveness of this optimization based fault diagnosis strategy.

Keywords: Fault diagnosis, nonlinear systems, moving horizon estimation, particle swarm optimization(PSO).

1 Introduction

Fault detection and diagnosis (FDD) is receiving more and more attention due to the increasing demands for higher safety and reliability of dynamic systems[1]. One of the main research topics is the model-based FDD systems, in which the design of FDD systems for linear systems has made remarkable progress in the past two decades and a well-established framework is now available[2, 3], and study on nonlinear FDD technique is still in progress[4].

It is pointed out that parameter estimation is an important and effective method for fault diagnosis, where the fault is described as some specific system parameters to be estimated and the change of parameters are detected to determine the fault[5]. For example, Zhou proposed a strong tracking filter to estimate the time-varying parameters of nonlinear system, and fault diagnosis is realized using modified Bayesian classification method[6].

Indeed, the parameter estimation problem could be translated into the optimization of complex objective functions as well as many other engineering problems. The well-known minimum variance estimation for linear system is to minimize the estimation error[7]. Based on the same principle, the nonlinear parameter estimation problem could also be solved. However, the objective function for linear case is convex with single extreme point; while that is more complex with multiple extreme points. Therefore, it is easy to be trapped into local optima using traditional gradient descent based optimization methods which are sensitive to the initial point.

The intelligent optimization algorithms proposed for global optimization of complex functions are hot in research recently. For instance, the evolutionary algorithm has been well studied in past years and have many applications in control areas such as controller design, system identification and fault diagnosis[8]. Particle swarm optimization (PSO) is a novel population-based searching technique proposed in 1995[9] as an alternative to genetic algorithm (GA). Its development is based on the observations of social behavior of animals such as bird flocking, fish schooling, and swarm theory.

As discussed before, it is intuitive to apply PSO for parameter estimation of nonlinear systems as well as GA[10]. In this paper, the standard PSO is improved by combining the simulated annealing (SA) algorithm[11], and the new hybrid algorithm is then called PSOSA. By introducing the probabilistic jumping property of SA, the premature convergence of PSO could be largely avoided. Considering the online computation demand for fault diagnosis, the framework of moving horizon estimation (MHE)[12, 13] is applied where fixed length of data are used for estimation purpose. Briefly, the fault diagnosis of nonlinear systems in this paper is based on the parameter estimation under MHE framework and the optimization procedure in MHE is solved by the presented hybrid PSOSA algorithm.

2 Moving horizon estimation

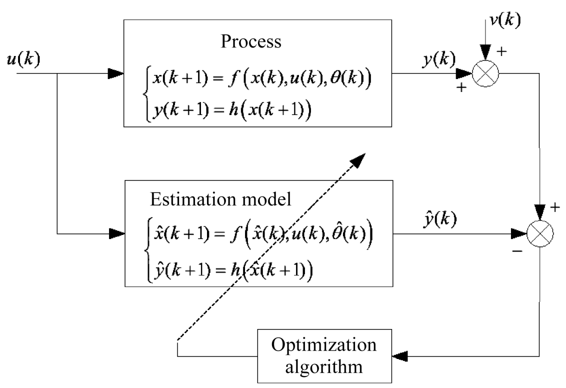

Fig. 1 Framework of parameter estimation

As mentioned in introduction that parameter estimation is an important strategy for fault diagnosis, where the ba-

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sic principle is to minimize the error between real output data and the predicted outputs over estimated parameters, such as the famous minimum variance estimation for linear systems[7]. However, the error function (objective function) for nonlinear parameter estimation is more complex, and the traditional gradient based optimization method would trap into local optima. Then some intelligent global optimization algorithms such as genetic algorithm was proposed for nonlinear parameter estimation[10], whose framework is illustrated in Fig. 1.

In Fig. 1, y and $\hat{y}$ are the real output and the estimated output, respectively; u is the system input signal; θ is the unknown parameter which is also the variable to optimize; and v is the measurement noises. The following mean square error is the often used optimization objective function

$$\min_{\hat{\theta}} J = \sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2. \tag{1}$$

However, fault diagnosis needs to monitor and make decision in real time, which makes online computation necessary. On the other hand, the system states are always unknown in practice. Therefore, the online state and parameter estimation is required for fault diagnosis. The main difficulty for online computation is the increasing of data, since it is impossible to use all data for optimization in (1). The framework of MHE was presented for online estimation, whose basic principle is shown in Fig. 2.

In Fig. 2, I_t^N represents all input and output data in the previous N sampling period at t, and the estimation results at $t-1$ as well. It is noticed that the length of data window is fixed, and the window is moving over time without increasing of data storage. Then the requirement for online computation and optimization is satisfied. And obviously, it is of great significance to detect and estimate the change of fault parameters in fault diagnosis; the MHE framework is appropriate for estimation of time-varying parameters by ignoring historical data.

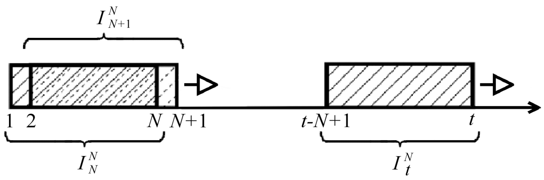

Fig. 2 Moving horizon estimation

Moving horizon estimation is the dual problem of model predictive control, and received much attention and wide study in past years. There are also some applications of MHE in fault diagnosis. Mignone *et al.* presented a moving horizon estimation and fault detection scheme for a class of hybrid systems[12], where each type of fault was also modeled as one mode of the hybrid system. All the states and modes were identified using MHE, and the fault was then detected. Similar to the well-known dedicated scheme for fault isolation, Tyler *et al.* proposed using a bank of MHE to estimate the system states and fault parameters for fault detection and isolation[13]. However, these works are mainly for linear systems.

In the following of this section, the description of MHE for online state and parameter estimation of nonlinear systems will be briefly given firstly. The detailed fault detection and isolation strategy will be discussed later. Consider the following nonlinear system with unknown parameter:

$$\begin{cases} x(k+1) = f\left(x(k), u(k), \theta\right) \\ y(k+1) = h\left(x(k+1)\right) + v(k+1) \end{cases} \tag{2}$$

where the parameter θ is assumed to be constant for simplicity. The fixed length of moving window is N. At the sampling time k, the initial state $x(k-N)$ and the unknown parameter θ are needed to be estimated, i.e., the optimization objective function at k is

$$\min_{\hat{x}(k-N|k),\hat{\theta}(k|k)} J = \sum_{i=k-N+1}^{k} \|y(i) - \hat{y}(i|k)\|^2. \tag{3}$$

We only need to estimate the initial state of the moving window, but the state estimation of other sampling time is obtained from system model (2), i.e., for $i = k-N+1, \cdots, k$,

$$\begin{cases} \hat{x}(i|k) = f\left(\hat{x}(i-1|k), u(i-1), \hat{\theta}(k|k)\right) \\ \hat{y}(i|k) = h\left(\hat{x}(i|k)\right) \end{cases}. \tag{4}$$

Intuitively, if θ represents the fault parameters, fault diagnosis could be realized under the MHE framework, which will be studied in Section 4.

3 Hybrid PSOSA optimization algorithm

The estimation problem described in the last section is essentially a multi-dimensional numerical optimization problem, and the optimization algorithm is used to adjust the state and parameter estimation. Due to the nonlinear property of complex systems, it is hard to estimate all unknown variables precisely. Moreover, from the viewpoint of optimization, there may be multiple local optima on the corresponding multi-dimensional optimization surface. Traditional methods, especially gradient decent based approaches, are easy to be trapped in local optima. Therefore, many intelligent global optimization techniques such as evolutionary algorithm[8, 10] were introduced to this field recently.

PSO[9] is a novel population-based searching technique as an alternative to genetic algorithm. Compared with GA, PSO has some attractive characteristics. Firstly, PSO has memory, that is, the knowledge of good solutions is retained by all particles, whereas in GA, previous knowledge of the problem is destroyed once the population changes. Secondly, PSO has constructive cooperation between particles, that is, particles in the swarm share their information. Recently, PSO has gained attention and applications by more and more researchers.

The updating formula of standard PSO is described as follows

$$V_i(k+1) = V_i(k) + c_1 r_1 \cdot (P_i - X_i(k)) + c_2 r_2 \cdot (P_g - X_i(k)) \tag{5}$$

$$X_i(k+1) = X_i(k) + V_i(k+1) \tag{6}$$

where V_i is called the velocity of particle i ($i = 1, \cdots, Pop$, where Pop represents the number of population); X_i is the position of particle i; P_i and P_g are the best historical position of particle i itself (i.e., local best position or its experience) and the best historical position of all particles (i.e., global best position or social experience); r_1 and r_2 are two independently uniformly distributed random variables with range $[0, 1]$; c_1 and c_2 are two positive constant parameters called acceleration coefficients to control the maximum step size; k represents the number of generations.

Similar to GA, the main deficiency of PSO is easy to prematurely converge. One reason is due to P_g used in (5), which causes all particles to tend to fly to the currently best solution that may be a local optimum or a solution near local optimum, so that all particles will concentrate to a small region and the global exploration ability will be weakened. It is known that SA[11] is a stochastic searching algorithm with probabilistic jumping property, where a worse solution has a probability to be accepted as the new solution. In particular, the probability is rather high when temperature is high and it decreases as the temperature decreases; and when the temperature tends to be zero the probability approaches to zero so that only better solutions can be accepted. Therefore, the premature convergence of PSO could be effectively avoided if the mechanism of SA is incorporated into PSO. A new hybrid optimization strategy called PSOSA was then proposed by us in [14].

As mentioned, the premature convergence of PSO is mainly caused by P_g, which is the best one among P_i. Intuitively, it is thought to replace P_g by one of the P_i (denoted by P_g'), and the global convergence property would be improved. The question is which P_i is to be selected as P_g'? Obviously, P_i with better quality should have a larger probability to be selected; especially, P_g (the best P_i) should have the largest probability to be selected. By borrowing the mechanism of SA, all other P_i can be regarded as special solutions that are worse than P_g, and we define $e^{-(F_i - F_g)/t}$ as the fitness value of each P_i to replace P_g at a certain temperature t, where F_i and F_g are objective values of P_i and P_g, respectively. Obviously, the largest fitness belongs to P_g and equals 1, while other fitness values are in interval $(0, 1]$. Then the whole procedure of PSOSA algorithm is given as follows[14]:

1) Initialization: Let $k = 0$; randomly initialize $X_i(0)$ and $V_i(0)$, and evaluate objective value F_i for all particles ($i = 1, \cdots, Pop$). Initialize P_i with a copy of $X_i(0)$ and initialize P_g with a copy of the best P_i. The initial temperature is set to $t(0) = -(F_l - F_g)/\ln(p_r)$, where F_g and F_l represent the minimal and maximal objective values, respectively.

2) Under current temperature $t(k)$, calculate the fitness for each P_i by the following formula:

$$Fitness(i) = e^{-(F_i - F_g)/t(k)}. \tag{7}$$

Then the selection probability of each P_i is given by

$$Pr(i) = \frac{Fitness(i)}{\sum_{j=1}^{Pop} Fitness(j)}. \tag{8}$$

3) For particle i ($i = 1, \cdots, Pop$), apply roulette wheel selection due to $Pr(i)$ to select P_g' from the set of all P_i, and then update V_i and X_i according to the following equations:

$$V_i(k+1) = \chi \cdot \{V_i(k) + c_1 r_1 \cdot (P_i - X_i(k)) + c_2 r_2 \cdot (P_g - X_i(k))\} \tag{9}$$

$$X_i(k+1) = X_i(k) + V_i(k+1) \tag{10}$$

where $\chi = \frac{2}{|2 - l - \sqrt{l^2 - 4l}|}$ and $l = c_1 + c_2 > 4$.

4) Evaluate new objective value F_i for all particles $X_i(k+1)$, and update P_i and P_g (including position and objective values).

5) If the end criterion is satisfied, then output the best solution P_g and its objective value F_g; otherwise, anneal the temperature: $t(k+1) = \alpha t(k)$, and let k = k + 1, then back to step 2.

Notice that at the early stage of evolution (i.e., the temperature is high), the fitness values of all Pi solutions are close to 1 so that all particles have almost an equal probability to be selected as P_g'. Thus, PSOSA shows strong global exploration in the whole solution space. As temperature decreases, the probability to select those solutions different from P_g decreases. And when the temperature tends to 0, only P_g is selected, so that PSOSA becomes the standard PSO. The mechanism of SA incorporated into PSO does not change the structure of PSO nor increases any function evaluation, but the selection of P_g' which improves the global convergence. The effectiveness of PSOSA and its advantages are shown in [14], where PSOSA is applied to the off-line parameter estimation problem.

4 Fault diagnosis using PSOSA

Applying the presented PSOSA algorithm for the optimization problem (3), the states and fault parameters could be estimated online for fault diagnosis. However, if there are many fault parameters, the optimization procedure will become difficult, especially when there exist disturbances and noises in practice. Then it will be hard to make decision on fault diagnosis.

The dedicated scheme is an effective strategy for fault detection and isolation, where a bank of observers are designed corresponding to every type of faults as well as the normal case. Similarly, we could also use a group of MHE for fault diagnosis, where MHE_0 is designed for state estimation of normal system and MHE_i is designed to estimate the states as well as the i-th fault parameter ($i = 1, \cdots, N$, where N is the number of all known fault types). The basic idea is to verify which MHE is the most suitable one for current system by comparing the optimization objective values of all MHE, where the minimum one would like to correspond to the matched MHE, and the fault is detected and isolated.

However, it is well known in identification theory that the lower order model is included by higher order model.

Since each fault model includes the normal model, the objective value of each MHE_i would be smaller than that of MHE_0 if we always obtain the global optima in all optimization procedures. Therefore, rather than directly comparing the value of (3), the performance of each MHE will be determined using Akaike's information criterion (AIC) which adds penalties for extra parameters as follows[13]:

$$AIC = n_y \cdot N \cdot \ln(J) + 2p \tag{11}$$

where J is defined in (3); n_y is the dimension of output y; p is the dimension of all decision variables to estimate. It is seen that the location of the optima will not change when replacing J by AIC, but the objective value is related to the complexity of model. Due to the added term $2p$, the AIC of MHE_0 would be smaller than that of any MHE_i before the fault happens. After the fault happens, the matched MHE_i would have the minimum AIC. Therefore, the fault detection and isolation logic could be described as follows:

$$\begin{cases} AIC_0 \text{ is the minimum} & \Rightarrow \quad \text{no fault} \\ AIC_i \text{ is the minimum} & \Rightarrow \quad \text{fault } i \text{ happened} \end{cases}$$

Another important aspect to apply PSOSA for optimization of MHE is the online computation requirement, since the intelligent optimization algorithm belongs to stochastic search algorithms which always need a lot of computations. But fortunately, it is not needed to obtain the accurate optima at each sampling time, because the key for fault diagnosis is to detect the change of status. That is, in a long period the status of system does not change, then we could divide the whole optimization procedure over time, where the generations of PSOSA at each sampling time could be largely reduced. Normally, the initial particles of PSOSA should be generated randomly. Here, we propose to generate the initial particles of the current matched MHE by the following way:

$$\hat{x}^0(k+1-N|k+1) = \tag{12}$$
$$f\left(\hat{x}^{opt}(k-N|k), u(k-N), \hat{\theta}^{opt}(k|k)\right)$$
$$\hat{\theta}^0(k+1|k+1) = \theta^{opt}(k|k) \tag{13}$$

where superscript *opt* represents the current optimal estimation (i.e., the last generation of particles); and superscript 0 represents the next initial generation of particles. Then obviously only a few of generations are needed at each sampling time to satisfy the requirement of online computation, and the optimization quality could be refined after several generations. Moreover, the initial particles of all other MHEs would also be randomly generated which guarantees the sparseness of particles to detect the change of system status after the fault happens.

5 Simulation

The simulation model is the DTS200 three-tank system, which is a benchmark in process control engineering[6]. Fig.3 shows the layout of the setup. The mathematical model of DTS200 is described as follows:

$$\begin{cases} A \cdot \mathrm{d}h_1/\mathrm{d}t = -Q_{13} + Q_1 \\ A \cdot \mathrm{d}h_3/\mathrm{d}t = Q_{13} - Q_{32} \\ A \cdot \mathrm{d}h_2/\mathrm{d}t = Q_{32} - Q_{20} + Q_2 \end{cases} \tag{14}$$

where

$$\begin{cases} Q_{13} = az_1 S_n \ \mathrm{sign}(h_1 - h_3)\sqrt{2g\,|h_1 - h_3|} \\ Q_{32} = az_3 S_n \ \mathrm{sign}(h_3 - h_2)\sqrt{2g\,|h_3 - h_2|} \\ Q_{20} = az_2 S_n \sqrt{2gh_2}. \end{cases} \tag{15}$$

The state is the levels of three tanks: $x = [h_1,\ h_3,\ h_2]^{\mathrm{T}}$; the input is the pump flow: $u = [Q_1,\ Q_2]^{\mathrm{T}}$; and the output vector is $y = [h_1,\ h_2]^{\mathrm{T}}$. The model parameters are $g = 9.81$ m/s^2, $az_1^0 = 0.5$, $az_3^0 = 0.45$, $az_2^0 = 0.6$, $A = 0.0154$ m^2, $S_n = 5 \times 10^{-5}$ m^2, $h_{\max} = 62 \pm 1$ cm, $Q_{1\max} = Q_{2\max} = 100$ ml/s. The levels of T1 and T2 are controlled by PI controllers with parameters $K_p = 0.001$ and $T_I = 5$ s. The model is discretized by Euler method with sampling time $T = 1$s. And the measurement noise is Gaussian with variance $R = 10^{-6} I_2$.

Two types of faults are considered here:

1) Leakage in T1: $Q_{leak}^1 = az_1 \pi r_1^2 \sqrt{2gh_1}$

2) Leakage in T2: $Q_{leak}^2 = az_2 \pi r_2^2 \sqrt{2gh_2}$

where r_1 and r_2 are the radii of leakage holes. The fault is assumed to happen at $T_f = 50$ s with $r_1 = 3$ mm and $r_2 = 2$ mm, respectively. The length of MHE is taken $N = 10$, and the parameters of PSOSA are $Pop = 20$ and $Gen = 30$.

Simulation results are illustrated in Figs.4~7. After the fault happened at 50 s, the levels of tanks are of little change due to the closed loop PI control and the fluxes of pumps are increased to compensate the leakage. It is shown that the fault is detected quickly, and the fault mode and corresponding parameter estimation are satisfactory under the measurement noises. Notice that there are some mistakes in fault mode before the occurrence of fault, which are caused by noises or bad optimization results in AIC. But these mistakes could be eliminated by smoothing the indexes of AIC, or simply by human judging whether it is a singular point or not.

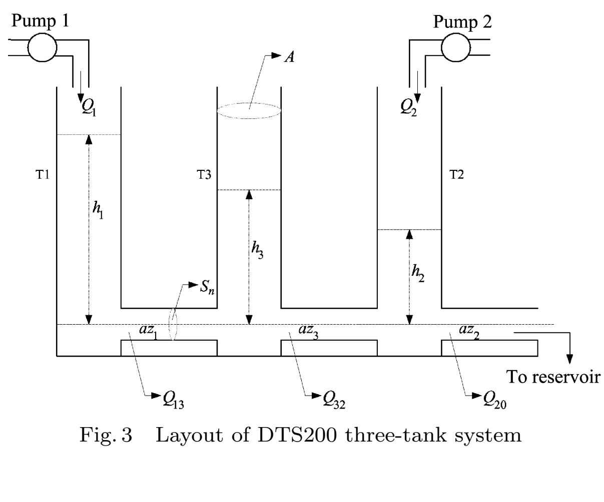

Fig. 3 Layout of DTS200 three-tank system

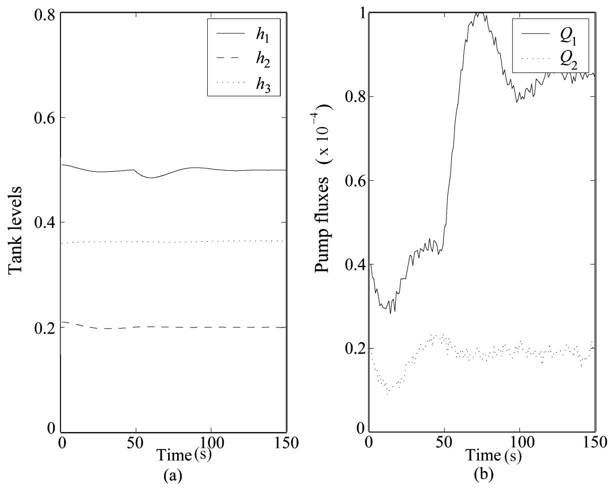

Fig. 4 Case 1: tank levels and pump fluxes

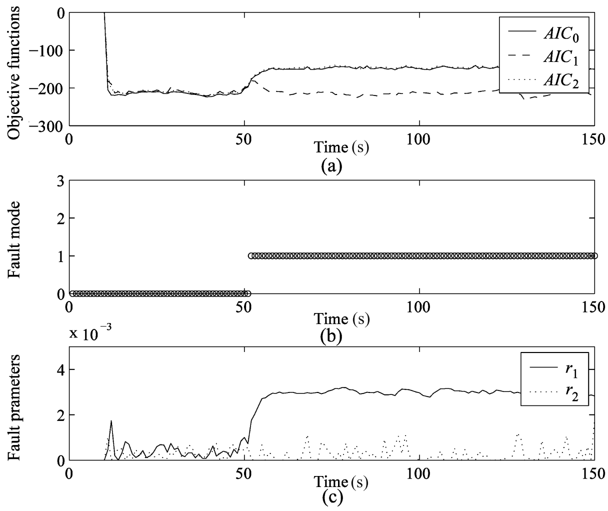

Fig. 5 Case 1: fault diagnosis result

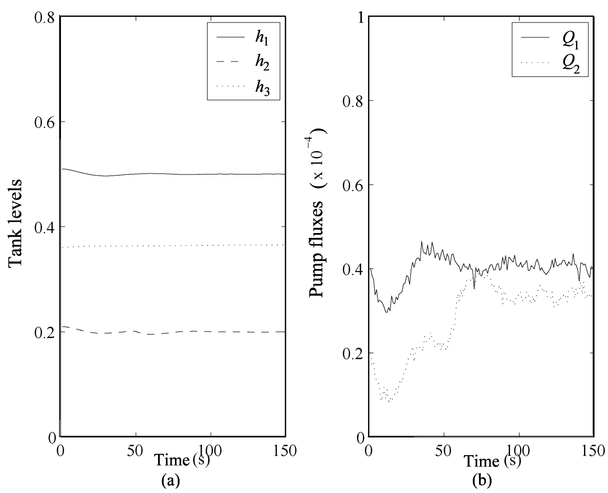

Fig. 6 Case 2: Tank levels and pump fluxes

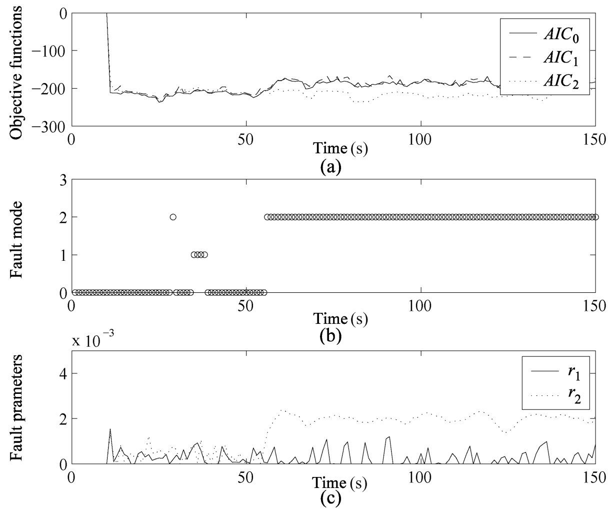

Fig. 7 Case 2: fault diagnosis result

6 Conclusion

A new hybrid intelligent optimization algorithm called PSOSA is presented in this paper for fault diagnosis of nonlinear systems. By incorporating the probabilistic jumping property of SA into standard PSO, the global convergence of PSO is improved. Based on the framework of moving horizon estimation, a group of estimator is applied for fault detection and isolation where the decision is made due to Akaike's information criterion. Simulations show the effectiveness of the PSOSA based fault diagnosis strategy.

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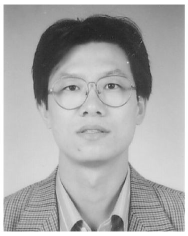

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