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Model Parameter Identification of FCC Reaction Regeneration System Based on Affine Bat Algorithm

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Abstract. In real industrial, due to the existence of measurement error, noise interference and other factors, the traditional bat algorithm can not effectively obtain the mathematical model of the actual system. In order to solve this problem, this paper proposes an affine bat algorithm. The bat algorithm is introduced to find the median of the optimal value range of the parameters, and the affine algorithm is used to calculated the value radius of the parameters. In order to make the radius shrinking more flexible, a new interval shrinking strategy was added. Then, the algorithm is applied into the catalytic cracking reaction regeneration system. The effectiveness of the proposed algorithm is verified by comparison with industrial field data.

1. Introduction

Fluidized catalytic cracking (FCC) is an important method to lighten heavy oil and plays an important role in petroleum refining industry. In recent years, approximately 18% of the world's crude oil processing capacity has come from catalytic cracking. The catalytic cracking process provides 30 to 40 percent [1] of the gasoline used in daily life. Therefore, the FCC has an important impact on the economic benefits of refineries. At the same time, it is particularly important to optimize the control system of the reaction regeneration system.

In real industrial, due to the existence of measurement error, noise interference and other factors, the first-order plus lag model [2] can not meet the design requirements of the controller. After determining the model structure of FCCU, finding a reliable model parameter estimation method becomes the key to determine the accuracy of the model. Jia [3] proposed an off-line model identification method, which requires identification of single input and single output processes one by one, so it takes a lot of computation. Ning [4] adopted the PPSO to identify the FOPDT model. None of the above methods consider measurement error and noise interference, so it is difficult to get the optimal value. Affine optimization algorithm [5] provides a systematic and effective method for parameter estimation. Therefor, the affine-bat algorithm is proposed to identify the FOPDT model of the FCC reaction-regeneration system, The algorithm can take the error into account, so that the interval parameters can be directly included in the calculation, and the error caused by the correlation between the variables can be eliminated, and the parameter calculation due to measurement error and noise interference is solved. The effectiveness of the proposed method is verified by simulation experiment.

2. Affine bat algorithm

2.1. Affine algorithm

The interval algorithm [6] ignores the correlation between variables in operation, which leads to the over conservatism of the algorithm. The affine algorithm can record the dependency relationship between variables, which makes the calculated results more compact than the interval algorithm, so affine algorithm is selected in this paper. The basic affine form is:

$$\hat{x} = x_0 + x_1\varepsilon_1 + \cdots + x_n\varepsilon_n = x_0 + \sum_{i=1}^{n} x_i\varepsilon_i \tag{1}$$

where x_0 is the central value of $\hat{x}$; $\varepsilon_i \in [-1 \quad 1]$ is the i th noise symbol, and its coefficient $x_i \in R$ is called the i partial increment of $\hat{x}$. Since $\varepsilon_i \in [-1 \quad 1]$ represents different noises and is independent of each other, the minimum and maximum values of $\hat{x}$ can be obtained when $|\varepsilon_1| = |\varepsilon_2| = \cdots = |\varepsilon_i| = 1$.

2.2. Bat algorithm

The bat algorithm is a new type of metaheuristic group intelligence optimization algorithm proposed by Professor Yang [7] in 2010. The algorithm is based on iterative optimization search technology, which far exceeds other algorithms in terms of accuracy and effectiveness, and there are not many parameters to be adjusted.

Based on the echolocation behavior of microbats, bat search algorithm adopts different pulse frequency and loudness. The algorithm idealizes echolocation of bats, summarized as follows: each virtual bat has a random flight velocity v_i at position x_i, while the bat has a different frequency or wavelength, loudness A_i, and pulse emissivity r. When the bat hunts and discovers prey, it changes the frequency, loudness, and pulse emissivity to select the best solution until the target stops or conditions are met. This is essentially the use of tuning technology to control the dynamic behavior of the bat colony, balancing and adjusting the parameters of the algorithm, in order to achieve the optimal bat algorithm.

2.3. Affine bat algorithm

Affine bat algorithm is based on bat algorithm as accelerator, which combines bat optimization algorithm with affine algorithm to improve search efficiency. The variables in the bat algorithm are replaced by intervals and used to update the formula. The optimized output is also an interval that satisfies certain conditions. The specific description of the affine bat algorithm is as follows:

(1) Initialization, including bat interval position and interval velocity. According to the definition of affine algorithm in literature [8], the space vector expression of the i th particle is:

$$v_i = \left(\left(\frac{v_1^l + v_1^u}{2} + \frac{v_1^u - v_1^l}{2}\varepsilon_{i1}\right), \cdots, \left(\frac{v_n^l + v_n^u}{2} + \frac{v_n^u - v_n^l}{2}\varepsilon_{in}\right)\right) \tag{2}$$

$$x_i = \left(\left(\frac{x_1^l + x_1^u}{2} + \frac{x_1^u - x_1^l}{2}\varepsilon_{i1}\right), \cdots, \left(\frac{x_n^l + x_n^u}{2} + \frac{x_n^u - x_n^l}{2}\varepsilon_{in}\right)\right) \tag{3}$$

where $\varepsilon_{i1}, \varepsilon_{i2}, \cdots, \varepsilon_{in}$ are mutually independent noise elements, and $\varepsilon_{in} \in [-1 \quad 1]$; n represents the dimension of the population, x and v represent the upper and lower bounds of particle position and velocity respectively.

(2) According to the fitness function, the optimal center fitness value of the current population and the optimal position of the current population are calculated.

(3) By random perturbation, the optimal central position and interval radius are updated, and then the optimal interval is obtained. See the flow chart in the next section for specific steps.

(4) One of the key steps of the algorithm is to reduce the interval width of the optimal particle when the optimal fitness interval does not meet the preset precision. This paper adopts an interval dynamic

contraction strategy, so define an interval contraction factor α , represents the degree of contraction of the interval. The larger the contraction factor is, the smaller the interval contraction is. The specific strategies are as follows:

$$X_{new} = \left[x^l + \frac{(x^u - x^l)}{2} * e^{-\alpha} \quad x^u - \frac{(x^u - x^l)}{2} * e^{-\alpha} \right] \tag{4}$$

The contraction radius is different in different stages. At the beginning, the interval width is large and the width changes obviously. However, as the optimization progresses, in the final search, the width decreases and all the intervals become too small. If the contraction radius is too large in the later stage, it is easy to skip the optimal fitness. In this case, the main effect of shrinkage is search speed, not search accuracy. So when the optimal fitness interval does not meet the preset accuracy, let $\alpha = \alpha + 1$, therefore, the contraction factor is increased and the contraction radius is reduced.

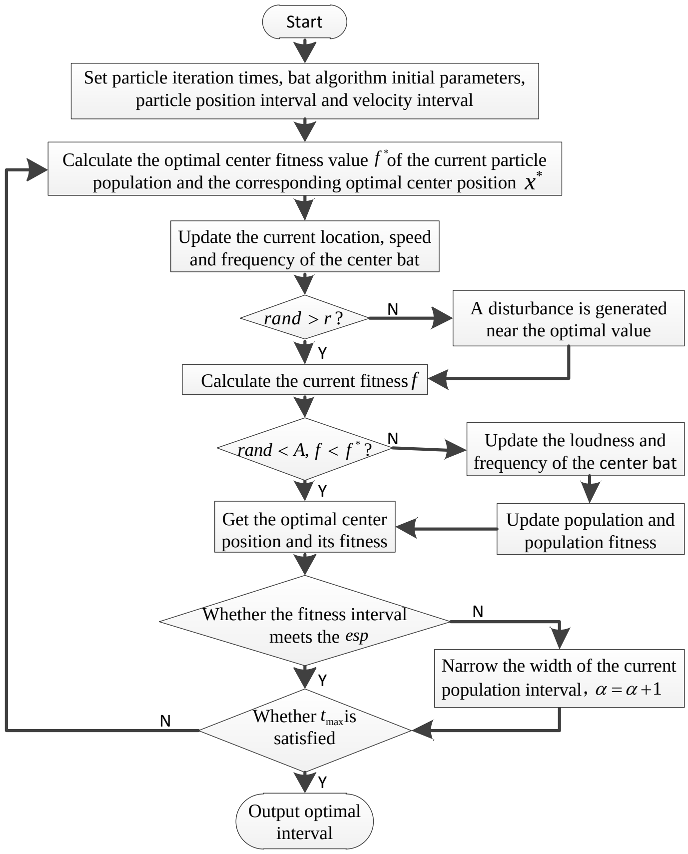

Figure 1. Flow chart of affine bat algorithm.

2.4. Algorithm flowchart

The affine algorithm and the bat algorithm complement each other. Every step of the algorithm shows the combination of the two. The flow of its algorithm is shown in figure 1.

3. Experiment and Analysis

In order to verify the effectiveness of the proposed algorithm, the algorithm is applied to the model parameter identification of catalytic cracking reaction regeneration system. FCC system has high efficiency, strong coupling and noise interference in the process, which leads to the uncertainty of parameters. Therefore this system is a good example to verify the effectiveness of the affine bat algorithm.

3.1. Simulation object

The industrial device studied in this paper is a set of FCC reaction-regeneration system device of Jiujiang Petrochemical. The mathematical model of FCC reaction regeneration system studied in this paper is identified based on the mechanism model established by Jiang [10].

In this paper, the FOPDT transfer function with double input and double output is selected as the FCCU model. The controlled variables are riser outlet temperature P_{re} and regenerator pressure T_{riser}, and the controlled variables are regenerated catalyst flow F_{rc} and regenerator exhaust gas discharge flow F_{re}. The transfer function model is as follows：

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} = \begin{bmatrix} \dfrac{K_{11}e^{-\tau_{11}s}}{T_{11}s+1} & \dfrac{K_{12}e^{-\tau_{12}s}}{T_{12}s+1} \\ \dfrac{K_{21}e^{-\tau_{21}s}}{T_{21}s+1} & \dfrac{K_{22}e^{-\tau_{22}s}}{T_{22}s+1} \end{bmatrix} U \tag{5}$$

where G_{11} and G_{22} are the main channel transfer functions; G_{12} and G_{21} are interference channel transfer functions; $\widehat{Y}_1$ and $\widehat{Y}_2$ represent T_{riser} and P_{re}; U_1 and U_2 represent F_{rc} and F_{re}. According to equation (11). There are 12 parameters to be identified, as follows:

$$P = \left\{K_{11}, K_{12}, K_{21}, K_{22}, T_{11}, T_{12}, T_{21}, T_{22}, \tau_{11}, \tau_{12}, \tau_{21}, \tau_{22}\right\} \tag{6}$$

3.2. Parameter identification

The affine bat algorithm parameter is set to: $t_{\max} = 200$, $n = 25$, $f_{\min} = 0.1$, $f_{\max} = 2$, $esp = 0.5$, $A = 0.25$, $r = 0.5$, $\alpha = 1.2$. The fitness function is selected:

$$fit = \left(\frac{1}{K} \sum_{k=1}^{K} \sum_{n=1}^{N} \left(\frac{z_n(k) - \overline{z}_n(k)}{z_{n,\max} - z_{n,\min}} \right)^2 \right)^{\frac{1}{2}} \times 100\% \tag{7}$$

where k is the sequence number of sampling, and t_k is the sampling time; K is the number of points sampled; n is the ordinal number of the output; N is the model output dimension; The value of the k sampling point output of the n process is $z_n(k)$, and the value of the k sampling point output of the n model is $\overline{z}_n(k)$; The smallest and largest values of the output of the n procedure are $z_{n,\min}$ and $z_{n,\max}$.

Matlab was used for parameter identification, and the identification results were as follows:

$$\begin{bmatrix} \hat{Y}_1 \\ \hat{Y}_2 \end{bmatrix} = \begin{bmatrix} \dfrac{[0.6151 \quad 0.6153]e^{[-0.0545 \quad -0.0551]s}}{[2.7152 \quad 2.7424]s+1} & \dfrac{[14.0154 \quad 14.1359]e^{[-3.8586 \quad -3.8974]s}}{[5.7827 \quad 5.8409]s+1} \\ \dfrac{[0.5455 \quad 0.5509]e^{[-2.3604 \quad -2.3842]s}}{[8.4854 \quad 8.5706]s+1} & \dfrac{[1.4113 \quad 1.4255]e^{[-8.0709 \quad -8.1521]s}}{[10.1288 \quad 10.2306]s+1} \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} \tag{8}$$

The obtained simulation results are shown in figure 4:

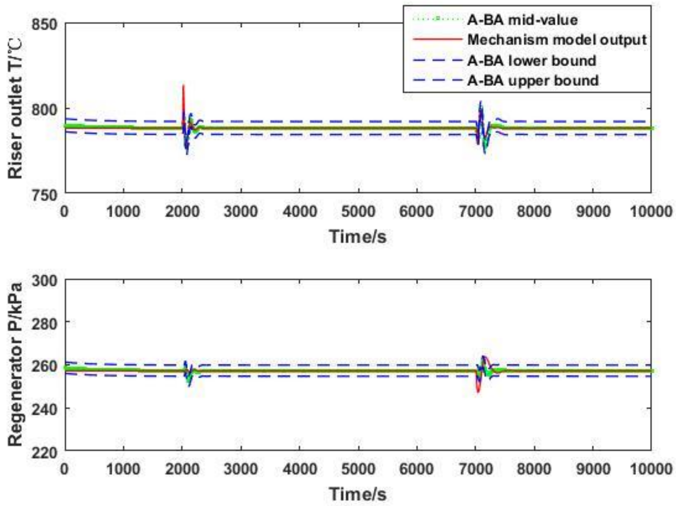

Figure 2. Output response curve of A-BA identification.

It can be seen from figure 2 that the output of the interval model obtained by the affine bat algorithm contains the output of the real model. It can be understood that the real system is contained in the interval model.

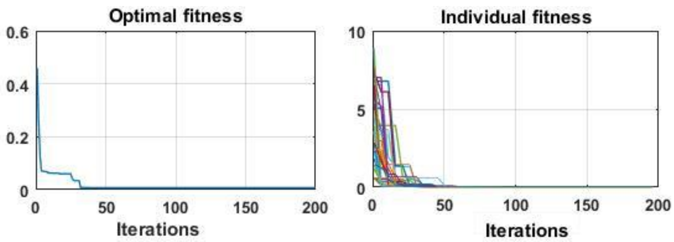

Figure 3. Iteration diagram of particle fitness value.

According to figure 3, the optimal adaptive value of the interval central value and the individual optimal value converge, when the affine bat algorithm reaches 40 steps.

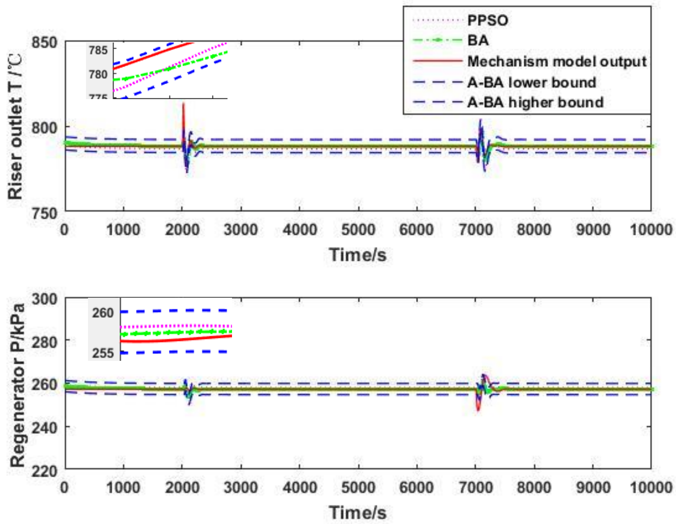

Figure 4. The output curves are identified under different algorithms.

In order to illustrate the advantages of the affine bat algorithm, figure 4 shows the comparison of the identification results of the perturbation particle swarm optimization algorithm (PPSO), the bat algorithm (BA) and the affine bat algorithm (A-BA). It can be seen from figure that PPSO and BA do not take into account the measurement error and noise interference, and will deviate from the real value at any time, which will bring uncertainty to the model of the catalytic cracking reaction regeneration system. The A-BA obtains the optimal solution interval by introducing the affine algorithm, and includes the real value in the interval, thus improving the calculation accuracy.

4. Conclusion

In this paper, based on the fact that bat algorithm can not effectively obtain the real model of the real industrial, affine bat algorithm is proposed. At the same time, the interval dynamic shrinkage strategy is used to approach the optimal solution interval continuously, which accelerates the convergence of the algorithm. Then the algorithm is applied to the parameter identification of the two-input, two-output FOPDT model of the FCC reaction regeneration system. Simulation results show that the real value is contained in the upper and lower bounds of the optimal range. This algorithm solves the problem of inaccurate parameter calculation caused by measurement error and noise interference. Finally, A-BA is compared with BA and PPSO to verify the accuracy and superiority of the algorithm in identifying the parameters of the FOPDT model of FCC reaction regeneration system, which lays a foundation for the subsequent research of FCC process.

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