The optimization of parameters for controlling iron ore sintering process based on maximum satisfaction

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Abstract: This research put forwards a stepwise parameter optimization approach based on maximum satisfaction aiming at the characteristics of multi-process control indices and cascading in iron ore sintering process. Given the sintering process involves multiple quality indices and the demand of reducing cost of first proportioning and the consumption of coking coal has to be met, we built a satisfaction evaluation function, based on which, an improved whale optimization algorithm(IWOA) is used to optimize control parameters. Simulation results indicate that the optimization approach of control parameters proposed in this research can effectively promote the quality indices of increasing sintering iron ore and decrease production cost.

1. Introduction

Steel industry usually uses iron ore as raw material, however, poor iron ore fails to be directly added into blast furnace and even seriously causes discontinued production. Therefore, poor iron ore prior to being added into blast furnace needs to be conducted briquetting process. In China, more than 90% of steel industry adopted sintering process[1], iron ore sintering is a process that several types of iron ore powders, flux and coking coal are put into blast furnace to conduct high-temperature calcination to further be sintered into lumps in the case of incomplete smelting. As sintering is seen as complex process involving multivariable, strong nonlinearity, the presence of multi-reaction, large time delay and strong coupling[2], operators participating in the sintering process are only able to perform non-specialized regulation according to their personal experiences in most of time. Hence, it is impossible for operators to timely and accurately optimize setting parameters by their experiences in the case of varying working conditions. Numerous studies have been carried out to solve the issues about complex sintering industrial process, literature[3] built a model of predicting sintering process based on BP neural network aiming at the strong nonlinearity characteristics of iron ore sintering used in production process and then employed genetic algorithm to solve the optimal operation parameters of sintering process. A study applied a genetic algorithm to optimize the operation parameters of the process of copper flash smelting due to copper flash smelting furnace having varying, complex and uncertain influencing factors[4]. They finally obtained operation parameters characterized by low energy consumption and reasonable technological indices. Considering nickel flash smelting process is characterized by strong coupling, being time-dependent and uncertainty, the literature[5] established a method of optimizing process parameters by integrating Fuzzy modeling and adaptive fuzzy Neural network technology, which was proved to exhibit preferable application performance. Currently, there is a lack of universally
applicable optimization method, therefore it is of significance to the optimization of the parameters of sintering process.

2. The technological process of sintering process

In sintering process, first proportioning was conducted. Total iron, silicon dioxide and other impurities are controlled within allowable range and low overall cost.

Afterwards, second proportioning was performed: solvents including quicklime, limestone and dolomite and coking coal were mixed with neutralized powder in the first proportioning according to a certain proportion. By doing so, total cost has to be minimized on the premise of making key elements of sintered ores reach the requirement. Additionally, the ignition temperature and moving speed of trolleys need to be further optimized so as to have other indices in the sintering process reaching the requirements.

3. The optimization of parameters for sintering process

As each of procedures in the iron ore sintering process all involves multiple parameters to be optimized, as well as constraints of inequalities and variable boundary, it is difficult to obtain feasible solution when using intelligent algorithms to optimize all parameters and it has little possibility to solving optimal solution and satisfied solution. In this research, an IWOA is adopted to optimize the parameters in the sintering process. In order to promote optimization efficiency of the intelligent algorithm, the optimization is conducted by dividing into two stages: at first, the parameters relating to proportion of ores in first proportioning process are optimized. The results satisfying the requirements of chemical compositions in first proportioning is seen as the feasible solution. Furthermore, chemical compositions (neutralized iron ore in first proportioning) corresponding to the feasible solution are used as the inlet parameters of second proportioning and the sintering process. Afterwards, we optimize the proportion parameters and adjustable parameters including ignition temperature and speed of trolleys in the sintering process at second proportioning stage. Furthermore, satisfaction function is used to evaluate the proportion parameters and adjustable parameters including speed of trolleys in the sintering process at second proportioning stage. By means of continuously coordinating optimization process, we acquire a set of adjustable parameters that enable the indices of iron ore sintering process reaching requirement and make other indices overall optimum.

4. The design of satisfaction evaluation function
In order to objectively and accurately assess the shortfalls and merits of optimized parameters in iron ore sintering process, it is necessary to construct an appropriate satisfaction evaluation function. Total iron content, alkalinity and rotary drum are three primary evaluation indices of evaluating the quality of sintered iron ores. For the purpose of reducing the costs of concentrates and coking coal, only satisfaction reach the optimum as some of the indices are contradictory.

Iron ore sintering process have three technological indices and overall evaluation function

\[
 f_{\text{index}} = \begin{cases} 
 \alpha_1 f_B + \alpha_2 f_B + \alpha_3 f_B ; & B_{c_{\text{min}}} \leq B_c \leq B_{c_{\text{max}}} \ (z=1, \ldots, 3) \\
 0 & \text{otherwise} 
\end{cases}
\]

where \( B_1, B_2 \) and \( B_3 \) denote three technological indices: \( f(B_1), f(B_2), \ldots, f(B_3) \), which are the function of technological indices \( (0 \leq f(B_z) \leq 1) \). \( B_{c_{\text{min}}} \) and \( B_{c_{\text{max}}} \) are the allowable maximum and minimum values of each technological index. Let \( f_{\text{index}} \) be zero when technological index exceeds allowable range, indicating technological index fails to reach the requirement. \( \alpha_1, \alpha_2 \) and \( \alpha_3 \) represent the weights \( \sum_{z=1}^{3} \alpha_z = 1 \) of the importance for each technological index and their values are set based on practical conditions and experts’ experiences. The greater the \( f_{\text{index}} \) value, the more preferable the technological index \( (0 \leq f_{\text{index}} \leq 1) \), showing the parameter is optimal.

Char is the mostly consumed energy in the sintering process and the evaluation function is expressed as Eq (2):

\[
 f_{\text{Resource}} = f(Coke) 
\]

The satisfaction evaluation function is written as Eq. (3)

\[
 f = \beta_1 \times f_{\text{Index}} + \beta_2 \times f_{\text{Resource}} 
\]

Where, the coefficients \( \beta_1 + \beta_2 = 1 \).

5. The IWOA based optimization of the parameters for controlling sintering process

Whales, as carnivorous animals, have a specific predatory behavior, which is called as bubble-net feeding\(^3\), based on which, Mirjalili et al., put forward a whale optimization algorithm (WOA)\(^7\). Due to word limits, traditional WOA in the literature \(^7\) is not further described in this research.

5.1 A local searching-based elitist-learning approach

To increase the convergence rate of the IWOA algorithm, each of generations in the evolution process all select elite individuals (15% < \( \zeta < 35\% \)) in \( \zeta \) to further conduct concrete local searching and is written as

\[
 \hat{X}(t+1) = \hat{X}(t) + \omega \times \frac{1}{\|\hat{X}(t)\|} (R \cdot \hat{X}(t)) 
\]

where \( R \) denotes chaotic variable \((1 \times D \text{ dimensions})\) in a \([-0.5, 0.5]\) interval, as shown in Eq (5), we obtain

\[
 RR_{d+n+1} = \mu \times RR_{d+n} \times (1 - RR_{d+n}) 
\]

\( d = 1, 2, \ldots, D \), \( D \) refers to the dimensions of variables, where chaotic initial value is \( 0 < RR_{d,0} < 1 \) ( \( RR_{d,0} \neq 0.25, 0.5, 0.75 \)).

\[
 R_{d,n+1} = RR_{d,n+1} - 0.5 
\]

Where \( n = 1, 2, \ldots, N \) \( N \) denotes the times of concrete local searching \( (1 < N < 30) \), and \( \omega \) is the
contraction coefficient ($\omega = 0.1 \times \frac{n}{N}$).

This local searching operation takes an elite individual as a center and then the careful multilayer searching is randomly performed at the region surrounding the individual. As the times of the searching increase, searching range is shortened, which is capable of efficiently increasing the possibility of the optimal solution in the region nearby sub-optimal solutions.

5.2 The operation of random mutation
The IWOA exhibits similar performance to other swarm intelligence optimization algorithms in the latter iteration stage: all whale individuals within a population are prone to converge to the region in which most whale individuals are present, which cause the loss of population diversity, eventually making the IWOA subject to a probability of premature convergence. Literature [8] proposed a genetic diversity mutation method to deal with the issues concerning premature convergence. In this research, some poorest whale individuals ($5\% < \delta < 15\%$ ) are conducted mutation as follows:

Assuming an individual $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$, if each of components of $X_i$ satisfies a stochastic number $rand() \geq \theta (0.6 < \theta < 1)$, we select an element $x_k(k = 1, 2, \ldots, d)$ in $X_i$ and then use a real number that is randomly generated within $[Xl_i, Xu_i]$ range to substitute the element $x_k$ in the individual $X_i$, so as to generate a new individual $X'_i = (x'_{i1}, x'_{i2}, \ldots, x'_{id})$.

6. Verification of simulation experiment
\(\alpha_1, \alpha_2\) and \(\alpha_3\) refer to 0.4, 0.3 and 0.3 respectively. \(\beta_1\) and \(\beta_2\) are 0.55 and 0.45. \(\mu = 4\), \(\zeta = 20\%\), and \(\delta = 10\%\). In order to directly compare the validity of the proposed method with that of artificial intelligent approach based on 50 groups of data. As shown in Table 1, the total iron content, alkalinity and rotary drum indices obtained using proposed optimization method are used as predicating values acquired by extreme learning machine. As displayed in the table, the quality indices of sintered iron ore can be effectively improved using the proposed optimization approach. The method is able to reduce the cost of first proportioning and proportion of coking coal, which means the decrease of energy consumption.

|                           | The proposed optimized approach | Artificial optimization intelligence |
|---------------------------|---------------------------------|--------------------------------------|
| Qualification rate of total iron content | 96%                             | 96%                                  |
| Qualification rate of basicity     | 94%                             | 86%                                  |
| Qualification rate of rotary drum composting | 96%                             | 88%                                  |
| The cost of first proportioning   | 411.25 Yuan per ton            | 415.98 Yuan per ton                  |
| Proportion of coking coal         | 4.92%                           | 5.13%                                |

7. Conclusions
This work proposed a stepwise optimization approach of iron ore sintering process. Considering the sintering process has multiple quality indices, and the cost of the proportioning and the consumption of coking coal have to be decreased, the satisfaction evaluation function is established. Afterwards, IWOA is used to optimize the parameters of controlling the sintering process. The simulation results show that the proposed method of optimizing parameters is able to effectively increase quality indices and reduce production cost.

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