Research on Data-driven Energy Efficiency Optimization for Copper Flash Smelting Process

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Abstract: - The characteristics of the copper flash smelting process include: multiple variable, nonlinearity, strong coupling, long delay and large fluctuations. With the development of computer technology and industrial automation, the complex industrial process has produced a large number of production data, which contains rich information for the mining of their patterns. In order to improve energy efficiency of the copper flash smelting process, this paper presents a method for minimizing energy consumption with meeting three technical indexes (matte grade, matte temperature and ratio of Fe to SiO_2) as a constraint. Our method is composed of two main parts: firstly, the least square support vector machine model (LS-SVM) is used to predict three technical indexes and we compare it with back propagation (BP) neural network; secondly, the comprehensive energy consumption model based on particle swarm optimization (PSO) is used to find the operational-pattern of lowest energy consumption. Experimental results on practical production data show that our energy efficiency optimization method can accurately predict three technical indexes and find the operational-pattern leading to the lowest energy consumption.

Key-Words: - Copper Flash Smelting; Energy Consumption; Energy Efficiency Optimization; Three Technical Indexes; Least Square Support Vector Machine (LS-SVM); Particle Swarm Optimization (PSO)

1 Introduction

Flash smelting is the main method of modern fire smelting, in which concentrate powder is mixed with air or oxygen in the flash furnace nozzle with the speed of 60~70m/s spraying into the high temperature reaction tower. Then it takes 2~3s to complete decomposition, oxidation and melting of sulfide. A mixed melt of molten sulfide and oxide down to the bottom of the reaction tower, clarifying the separation of sulfur and slag, and eventually forms the matte and slag. There are three important technical indexes used to evaluate this process: matte grade, matte temperature and ratio of Fe to SiO2. In the process of copper flash smelting, they are not measured online.

In order to solve the optimization control problem of complex industrial process, a lot of research work has been carried out and some good results have been obtained [1-4]. The industrial application of these results plays an important role in stabilizing production. However, the energy consumption factor has been neglected and the mathematical model for optimizing the comprehensive energy consumption is absent in previous studies [2-5]. In our work, we take energy consumption as well as technical indexes into account. To the best of our knowledge, this method is the first try in combining these two aspects for such an optimization problem.

With the rapid development of network technology and the significantly improved basic automation, the copper flash smelting process accumulated a large number of industrial operation data, including rich potential information of the relationship between operation rules and process parameters. It provides favorable conditions for optimizing the production process control [6-9].

In view of the above problems, this paper proposes a method of energy efficiency optimization for the copper flash smelting. We fuse the production data from different data sources into operational-pattern and use evolutionary algorithms to train prediction model for three technical indexes. Then we take the lowest energy consumption and the optimal working condition as the target to find the best operational-pattern, which can not only stabilize production but also save energy. Combined with the reallife production process of an enterprise of copper flash smelting, it is proved that the mathematical model can well be used in copper flash smelting process.

2 Related work

The operating state of the complex industrial processes is often determined by the process parameters which are coupled with each other. In order to find the parameters that closely correlate to three technical indexes, Hu proposed the concept of operational-pattern [1]. It contains input conditions (feeding quantity, material composition, moisture content of the copper concentrate) and operating parameters (energy parameters like oxygen, air distribution, gas etc).

Considering the difficulties of modeling and online-measurement of technical indexes in copper flash smelting process, Gui proposed a data-driven operational-pattern optimization method [2]. Firstly, the data-driven prediction model of three technical indexes is established in their work. If technical indexes are not excellent, then a chaos pseudo parallel genetic algorithm is proposed to mine an optimal operational pattern from the optimized operational-pattern base to implement the optimal control of the smelting process. We also use the operational-pattern model to preprocess our data format. However, unlike the previous approach, we introduce an improved model of energy efficiency optimization. It can not only guarantee the stability of technical indexes, but also reduce energy consumption.

Xie used least square support vector machine (LS-SVM) to train prediction model for three technical indexes, and fulfilled the real-time prediction of them [10].

Similar to previous techniques, our work also contains the prediction model. Through a lot of historical production data, we find parameters of the highest correlation with three technical indexes and form an operational-pattern with these parameters, then we take the operational-patterns as input and three technical indexes as output of the train model. Our prediction model is presented in Section 3.1. Then a new model for energy efficiency optimization is presented in Section 3.2. Finally, results are presented and validated in Section 4, and Section 5 gives the conclusions.

3 Our method

The basic idea of the energy efficiency optimization algorithm is that given the feeding quantity, material composition, moisture content etc. of copper concentrate, and three technical indexes are stable under the premise of the expected value, we find the optimal assigned value of oxygen, air distribution, gas etc. to achieve the lowest energy cost and the best working conditions. As three technical indexes are not measured in real time and we need to evaluate the quality of the optimized conditions, therefore, this paper presents the optimization control framework based on the prediction model of three technical indexes and the optimization model for energy efficiency to optimize the production process. Frame structure diagram is shown in figure 1.

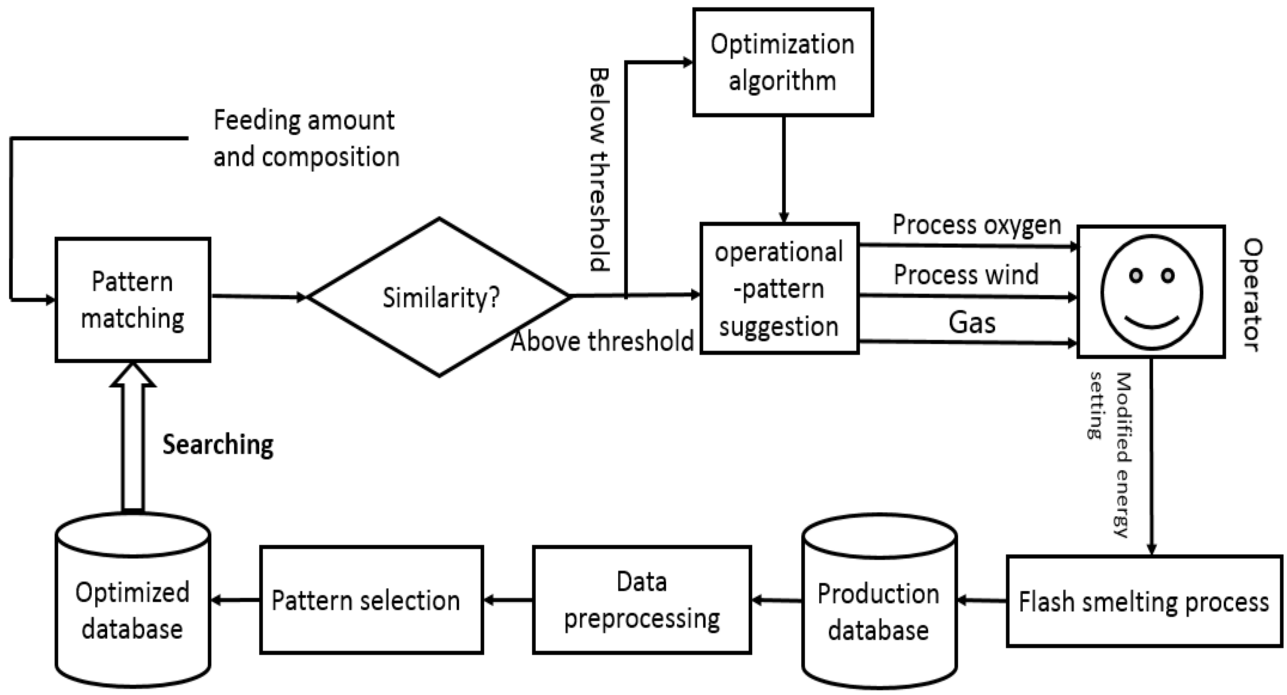

Figure 1: Frame of our full algorithm

Before the whole frame is running, we use the excellent working conditions of the historical production data to construct the optimized operational-pattern database and cluster them. The frame starts when the production conditions change or the performance of the current working condition do not meet the requirements. Our full algorithm consists of two main steps——searching, constraint-based optimizing.

We firstly compare the current production condition with all the data samples of the constructed database, for simplicity, we only compare the current production condition with each cluster's center and finally find the cluster of the highest similarity. The similarity of operational-pattern is defined as the exponent of the weighted Euclidean distance of the vector which is composed of the input condition. Secondly, to find the lowest energy consumption and the optimal working condition, we propose a constraint-based approach to get the most suitable operating parameters.

3.1 Prediction model

Due to the restriction of existing detection equipment, three technical indexes are obtained with serious lag. The operator can hardly get the feedback of technical indexes in real time after adjusting the operating parameters. Therefore, in order to solve the problem, we present a new hybrid model to predict three technical indexes in real-time. Another role of our prediction model is the constraint condition of next energy efficiency optimization.

The input of our prediction model consists of seven parameters which are copper, sulfur, iron, silica and water content of the copper concentrate, the concentration of oxygen enrichment, the oxygen per ton ore. Let x_i (i=1,2…7) be the seven parameters. Then, we obtain the following equation

$$x_i = \begin{cases} m \bullet p_i & \text{if } 1 \le i \le 5 \\ \dfrac{a_1 + a_2 + b \bullet (a_3 + a_4)}{\sum_{j=1}^{4} a_j} & \text{if } i=6 \\ \dfrac{a_1 + a_2 + b \bullet (a_3 + a_4)}{m} & \text{if } i=7 \end{cases} \tag{1}$$

where m denotes the quantity of concentrate, p_i denotes the corresponding mass fraction, a_j (j=1,2,3,4) respectively denotes process oxygen, central oxygen, process air and distribution wind, b denotes the proportion of oxygen in the air and it is always set to 0.21. Actually, we obtain a_j (j=1,2,3,4) from the data mining system.

The output of our prediction model is three technical indexes. For example, we put the matte grade as output. Then we use LS-SVM and the BP neural network to train the prediction model. In experimental simulation, we choose the radial basis function (RBF) kernel function for the LS-SVM regression model; In the BP neural network, we set the hidden layer neuron number to 20 and use S type tangent function Tansig for the hidden layer neurons and linear function purelin for output layer neurons.

3.2 Optimization model

Most complex industrial process optimization control problems can be summed up as a mathematical programming problem. In practical production, we generally find the optimal solution of the problem under the restriction of technical indexes, energy supply and equipment capacity etc. The target of energy optimization for copper flash smelting process is that given the input condition we find out an optimal energy setting scheme to make energy consumption lowest. Finally, the optimized energy setting values of process air, air distribution, process oxygen, central oxygen and gas are given by our optimization model.

In building our optimization model, we take into account the working condition S because our optimized result may cause boundary values of technical indexes if we only pursue the lowest energy consumption. S can be written as follows

$$\begin{cases} S = \sum_{i=1}^{3} \beta_i \bullet \left(1 - \dfrac{V_i}{V_{oi}}\right)^2 \\ \sum_{i=1}^{3} \beta_i = 1 \end{cases} \tag{2}$$

where V_i denotes the prediction value of matte grade, matte temperature and ratio of Fe to SiO_2, V_{oi} denotes the expected value of each technical index. In practical production, the expected values are 0.68, 1300ºC, 1.30. β_i denotes the weight of each technical index and we set to 0.4, 0.3, 0.3 according to manual experience.

From the above formula we know that the value of S is smaller and the performance of the working condition is better. According to the value of S, we can divide the working condition into four grades. In our algorithm, we use the excellent working conditions of the historical production data to construct the optimized operational-pattern database and cluster them.

Table 1: Division of working conditions

S	Grade
$0 \le S \le 0.002$	Excellent
$0.002 < S \le 0.01$	Good
$0.01 < S \le 0.04$	Medium
$S > 0.04$	Poor

Based on the prediction model, our combined optimization model for energy consumption and working condition can be written as formula (3). Three technical indexes V_i (i = 1, 2, 3) respectively denote matte grade, matte temperature and ratio of Fe to SiO2 and they are the constraints in our optimization model. We can calculate working condition S by formula (2).

$$\begin{cases} \min E = e + \mu \bullet S \\ e = \sum_{i=1}^{5} \frac{\alpha_i \bullet r_i}{M_f} \\ \forall i = 1, 2 \ldots 5, r_i \in [0,1] \end{cases}$$
$$s.t. \tag{3}$$
$$\begin{cases} 0.66 \le V_1 \le 0.70 \\ 1280 \le V_2 \le 1320 \\ 1.30 \le V_3 \le 1.50 \end{cases}$$

where E denotes optimization objective, α_i denotes standard coal conversion coefficient for each energy source, r_i denotes the normalized energy values and the five energy sources are process air, air distribution, process oxygen, central oxygen and gas, M_f denotes the feeding quantity of dry ore, μ denotes the penalty coefficient for the performance index of the working condition.

Finally, to solve the mathematical programming problem, PSO algorithm is used to optimize by using a population of candidate solutions, here dubbed particles, and each particle's movement is influenced by its local best known position and is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions. We update each particle's speed and new position according to formula (4).

$$\begin{aligned} v_{id}(t+1) &= w \bullet v_{id}(t) + c_1 \bullet r_1 \bullet (p_{id} - x_{id}(t)) + c_2 \bullet r_2 \bullet (p_{gd} - x_{id}(t)) \\ x_{id}(t+1) &= x_{id}(t) + v_{id}(t+1) \end{aligned} \tag{4}$$

where v_{id} is the particle velocity, x_{id} is the current particle (solution), p_{id} indicates the best position of the current particle have reached and p_{gd} are defined as the current global optimal solution, $r_1$and r_2 are random numbers between (0,1), w denotes inertia weight, c_1, c_2 are learning factors and usually c1 = c2 = 2. In standard PSO, inertia weight and learning factors are always set as constant. Particles are easy to converge to local extreme value. In our improved model, inertia weight and learning factors are set to variables. Inertia weight w can be written as

$$\begin{cases} w = w_1 + \frac{i}{T-1} \bullet (w_2 - w_1) \\ \forall i = 0, 1, 2 \ldots T-1 \end{cases} \tag{5}$$

where T denotes the maximum iteration number, w_1 denotes initial inertia weight of iteration and w_2 denotes inertia weight at the end of iteration. In experiment, w_1 and w_2 are set as 0.9 and 0.4 respectively.

The learning factors are updated using the inverse sine function and written as

$$\begin{cases} c_1 = c_{1\min} + (c_{1\max} - c_{1\min}) \bullet [1 - \frac{\arc\ \cos(-2i/(T-1)+1)}{\pi}] \\ c_2 = c_{2\max} - (c_{2\max} - c_{2\min}) \bullet [1 - \frac{\arc\ \cos(-2i/(T-1)+1)}{\pi}] \\ \forall i = 0, 1, 2 \ldots T-1 \end{cases} \tag{6}$$

where c_{1max} andc_{2max} are values of learning factors at the end of iteration, c_{1min} andc_{2min} are initial values at the beginning of iteration. In experiment, c_{1max} and c_{2max} are both set to 2.5, c_{1min} and c_{2min} are set to 1.0.

4 Results

In the experiment, we select 2284 groups of industrial production data from copper flash smelting process, and 90 groups are test data set, the others are training data set. Each group of data is a 10 dimensions vector. The first 7 dimensions are input of our train model and the last 3 dimensions are three technical indexes.

In this section, we present and evaluate our method in terms of maximum relative error and mean relative error of the prediction of three technical indexes. Then we make a comparison of the prediction results with BP model. Finally, we use our improved PSO algorithm to give the optimized energy results and compare them with standard PSO.

4.1 Prediction of three technical indexes

We first use BP neural network because it requires a known, desired output for each input value in order to calculate the loss function gradient and it is very suitable for our problem. In the experiment, the hidden layer neuron number is set to 20, learning rate is set to 0.1, minimum prediction error is set to 0.00001 and maximum iteration number is set to 2000. Figure 2, 3, 4 show test results of three technical indexes by using BP neural network.

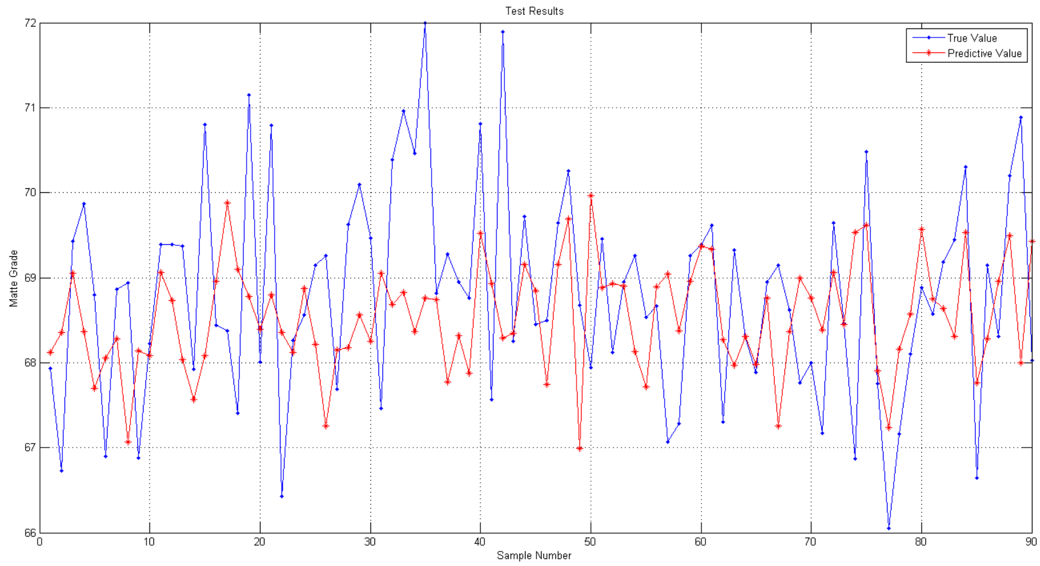

Figure 2: Prediction of matte grade by BP

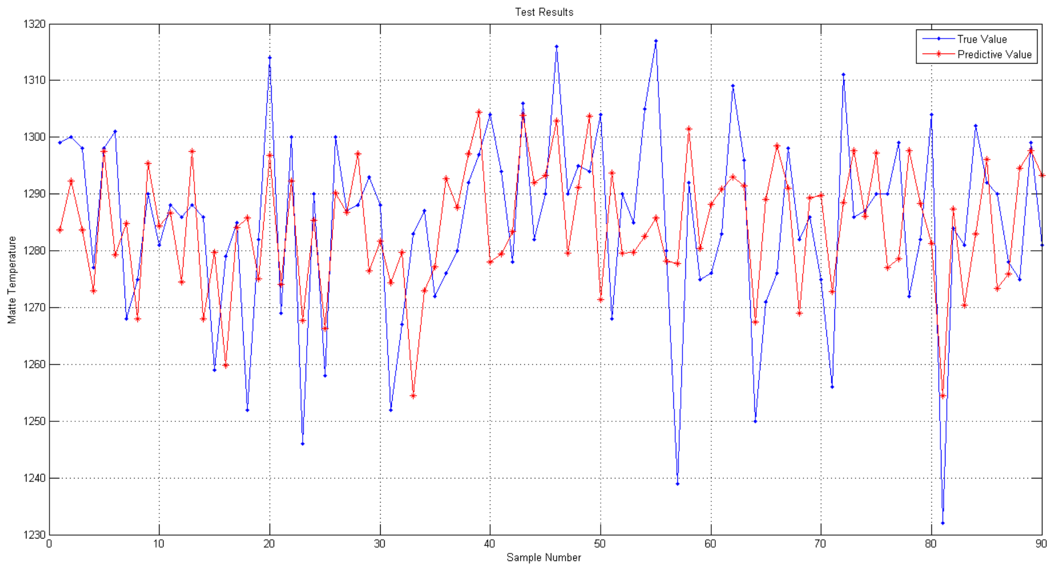

Figure 3: Prediction of matte temperature by BP

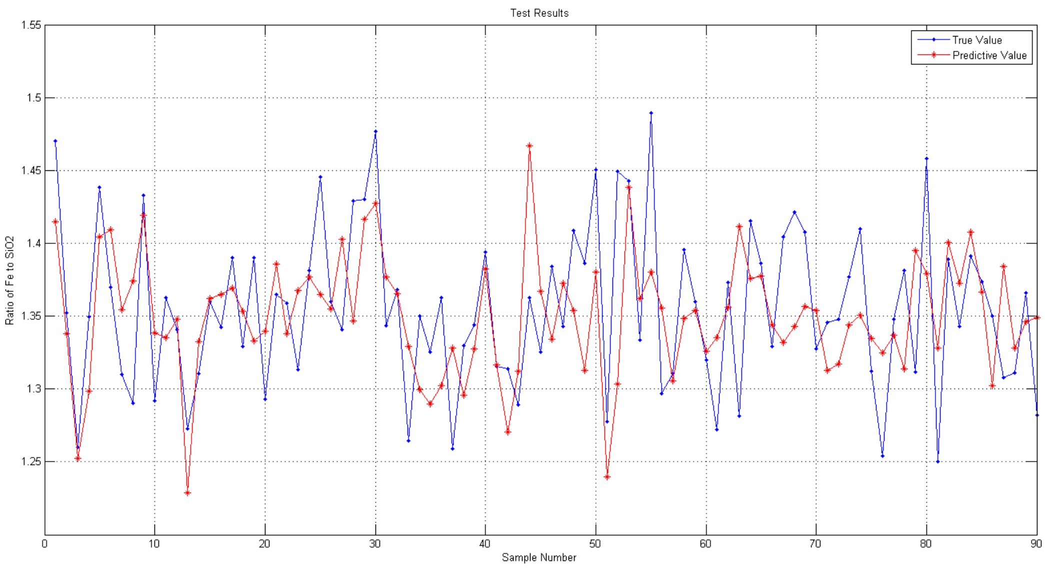

Figure 4: Prediction of Fe/SiO_2 by BP

In fact, our prediction problem can be considered as a regression problem. Then SVM is used to train the prediction model for three technical indexes. In SVM, there are a lot of kernel functions can be chosen. The RBF kernel function is used in experiment because it has good statistical properties. LS-SVM is also a set of related supervised learning methods and in this version one finds the solution by solving a set of linear equations instead of a convex quadratic programming (QP) problem for classical SVM, so it simplifies the computation complexity and has a more rapid calculation than classical SVM. Figure 5, 6, 7 show test results of technical indexes by using LS-SVM.

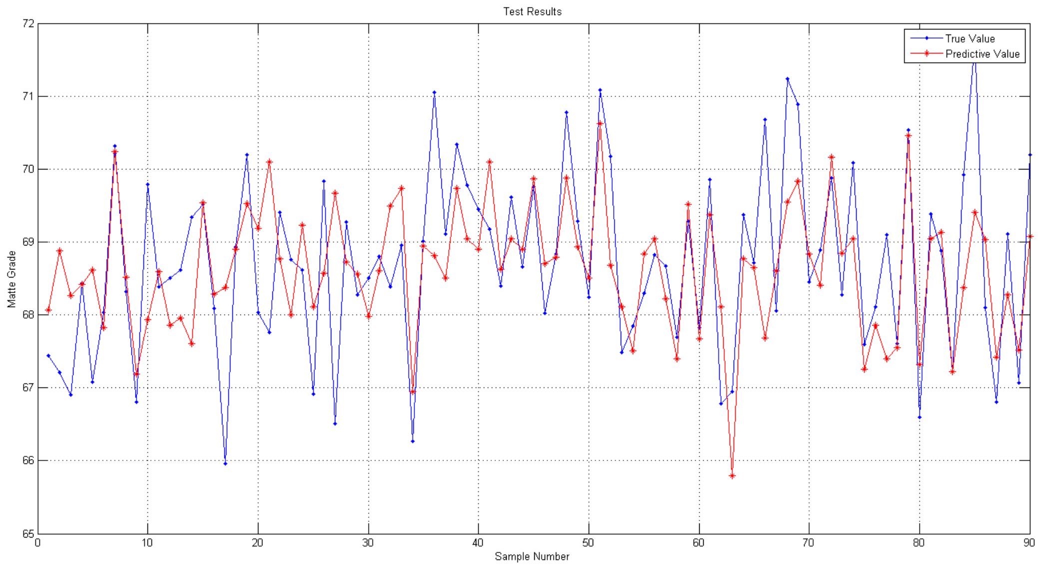

Figure 5: Prediction of matte grade by LS-SVM

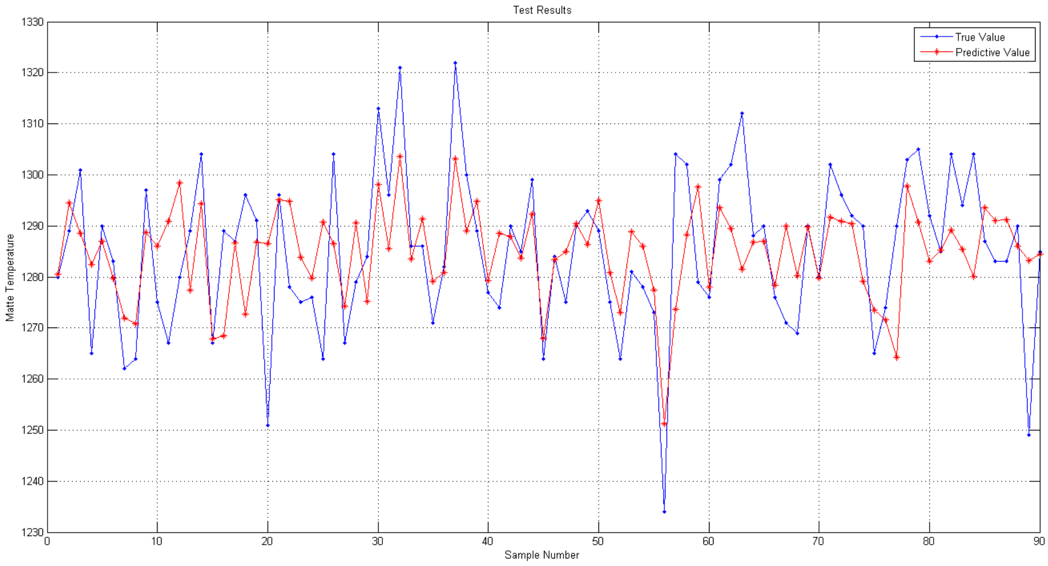

Figure 6: Prediction of matte temperature by LS-SVM

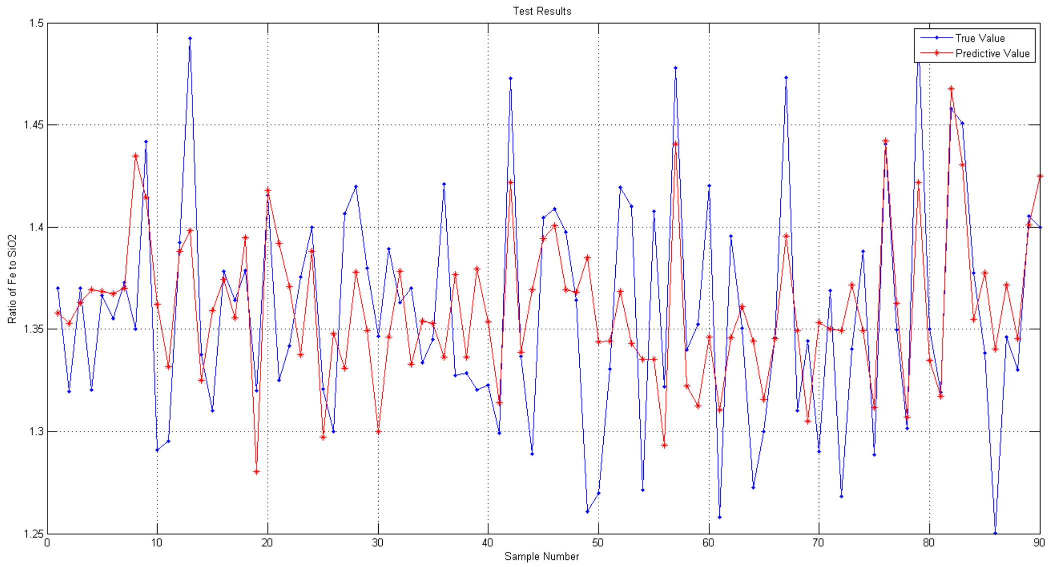

Figure 7: Prediction of Fe/SiO_2 by LS-SVM

Then we calculate maximum relative error and mean relative error for three technical indexes by BP neural network and LS-SVM. From these numerical results we first note that LS-SVM can predict three technical indexes with higher accuracy. Using BP neural network does not necessarily bring better performance because its learning speed is slower and the possibility of training failure is relatively larger. So in the energy efficiency optimization we select LS-SVM to train our prediction model.

Table 2: Maximum relative error and mean relative error for three technical indexes

Model	Matte Grade		Matte Temperature		Ratio of Fe to SiO2	
	Maximum Relative Error	Mean Relative Error	Maximum Relative Error	Mean Relative Error	Maximum Relative Error	Mean Relative Error
BP	5.27%	1.52%	3.04%	0.97%	11.19%	3.07%
LS-SVM	4.53%	1.10%	2.76%	0.76%	8.96%	2.59%

4.2 Energy optimization

We randomly choose fifty from all samples as test set. Then we match the current working condition and take formula (3) as the optimization objective. The matching cluster consists of operational-patterns and through which E is calculated by summing energy consumption and working condition index S. The former prediction model for three technical indexes is used to calculate S. If E is smaller than the current value, it is updated. In the experiment, the maximum iteration number is set to 100. Figure 8 shows the results before and after optimization by Standard PSO (SPSO). Vertical coordinate represent energy consumption e and horizontal coordinate represent sample number. Then we use the Improved PSO (IPSO) to optimize comprehensive energy consumption. Figure 9 shows the results based on IPSO.

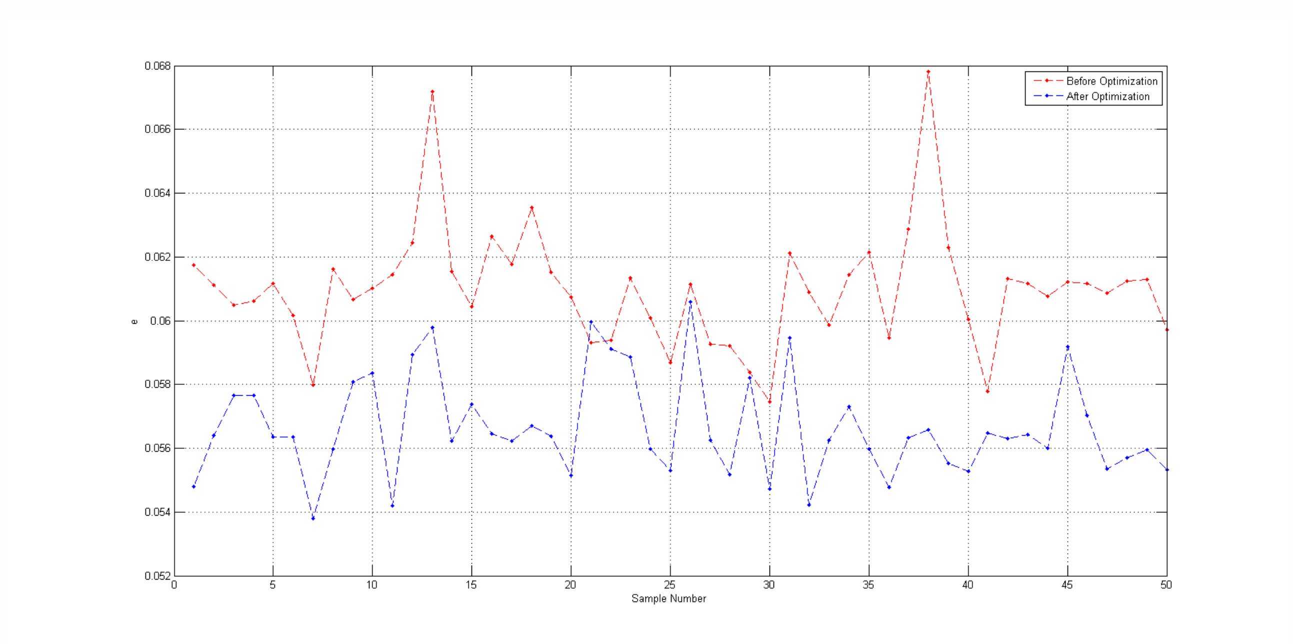

Figure 8: Optimization results based on SPSO

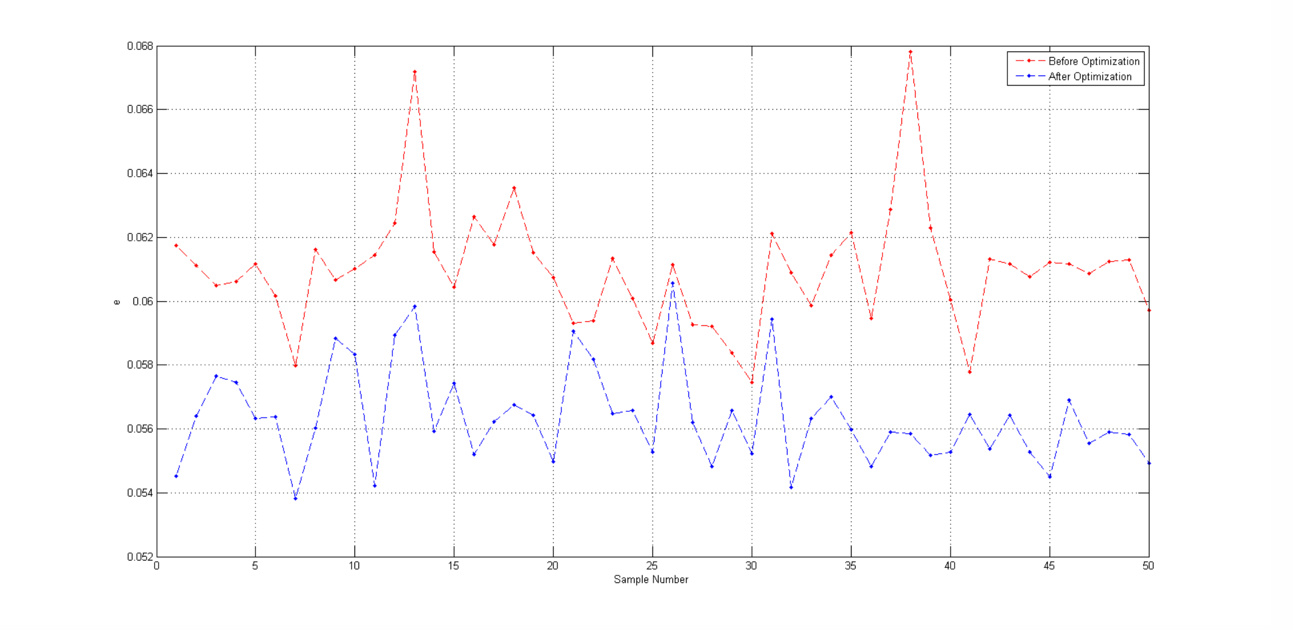

Figure 9: Optimization results based on IPS

In order to measure the optimization results of our method, we need an indicator called the energy saving rate η. We firstly sum the value of comprehensive energy consumption e of all test samples before and after optimization, then let the former minus the latter, and then devided by the former. Then, the energy saving rate η can be described as formula (7).

$$\eta = \frac{\sum_{j=1}^{50}[oriE(j) - optE(j)]}{\sum_{j=1}^{50} oriE(j)} \bullet 100\% \tag{7}$$

where oriE and optE respectively denote the energy consumption of each sample before and after optimization. Then we calculate the energy saving rate are 7.12% of SPSO and 7.60% of IPSO.

The experiment results show that IPSO has a better performance than others. In PSO algorithm, learning factors reflect the information exchange between particles. At the beginning of the algorithm, the particles mainly refer to their own information, but at the late stage, the particles are more focused on the social (Group) knowledge. So we make inertia weight w decrease linearly. However, we use the inverse cosine function to make c1 decrease and c2 increase nonlinearly because relative to the former, a larger value of c1 will make particles wandering in local and a larger value of c2 will cause the particles to converge to the local optimal value too soon. Experiment results confirm that our idea is correct and facts have proved that our improved model is both robust and efficient.

However, the limitation of our method is that predicting ability of the prediction model turn to decrease with the production process changed, and it needs a lot of samples and time to retrain. It is considered to establish a predictive correction model in the future to improve the predicting performance of our full optimization model.

5 Conclusion

In this paper, a new comprehensive energy efficiency optimization method is presented for reducing energy consumption. In the method, we first train the prediction model for three technical indexes which has a big impact on our optimization model. In optimization model, three technical indexes act as punishment item of optimization function. We find out the most similar operational-patterns from the optimized operational-pattern database as the initial solution, then we optimize the objective function by IPSO. The experimental results show that our method can reduce energy consumption and it has certain guiding significance for the copper flash smelting process optimization control.

Acknowledgements

The work in this paper is supported by The Special and Major Subject Project of the Industrial Science and Technology in Fujian Province 2013 (the Special Subject Project No. is 2013HZ0004-1), and supported by 2014 Key Project of Anhui Science and Technology Bureau–"Development and Application of Energy Efficiency Monitoring, Evaluating and Optimizing Control System for Flash Copper Smelting Enterprises" (Number: 1301021018).

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