ICSTI
6th International Congress on the Science and Technology of Ironmaking - ICSTI
42nd Ironmaking and Raw Materials Seminar/ 42º Seminário de Redução de Minério de Ferro e Matérias-primas
13th Brazilian Symposium on Iron Ore/ 13º Seminário Brasileiro de Minério de Ferro
ISSN 2176-3135

AN EVALUATION SYSTEM FOR IRON-MAKING PROCESS[1]

Lei Lei[2]
Xuewei Lv[3]
Chengguang Bai[4]
Xiaobo Huang[5]

Abstract
To solve the problem of irrational utilization of ore materials in iron enterprise, an evaluation system for iron-making process was built, which comprised material management module, ore proportioning module, granulating module, sinter module and blast furnace module. In this system, the simple method was introduced to calculate the optimum ore ratios; the neural network was used to predict the properties of products; the heat and material calculation was implemented to work out the economic and technical indices. On the other hand, iron-making evaluation software was developed and implemented at some iron enterprises in China. The results indicate that the evaluation system is reasonable, by which the economic and technical indices for the iron-making are worked out and the utilization efficiency of multiple ores could be improved.
Key words: Iron-making process; Hierarchical information; Evaluation system; Economic and technical indices.

[1] *Technical contribution to the 6th International Congress on the Science and Technology of Ironmaking – ICSTI, 42nd International Meeting on Ironmaking and 13th International Symposium on Iron Ore, October 14th to 18th, 2012, Rio de Janeiro, RJ, Brazil*

[2] *Master Student in College of Materials Science and Engineering, Chongqing University, China; leilei19870101@sina.com.*

[3] *Associate Professor in College of Materials Science and Engineering, Chongqing University, China; lvxuewei@cqu.edu.cn.*

[4] *Professor in College of Materials Science and Engineering, Chongqing University, China; bguang@cqu.edu.cn.*

[5] *Master Student in College of Materials Science and Engineering, Chongqing University, China.*

ISSN 2176-3135

1 INTRODUCTION

During the past decade, the price of iron ore kept a dramatic increase rate due to two main facts: one was the increasing need for iron ore with the development of iron and steel industry in China, and the other one was the decrease of high-quality ores all over the world. Thus, the cost of raw materials has been taken up a high fraction in the economic benefit of enterprises. As a result, varieties of low-grade ores or high harmful elements containing ores were used in the iron-making process which led to a wide fluctuation in chemical composition and physical properties of the mixture.
The topic of how to keep a good quality of product with low cost has been an urgent issue in the plants. The iron-making,(1-8) owing to its long process, non-linearity and random fluctuations, is not convincingly amenable to a single mathematical model. So many experts and reseachers undertook their researches on one or some of the steps in the iron-making process, and few of them pay their attention on the whole process which refers to the flow sheet from ore to the hot metal. In sintering, the ore blending calculation was undergone by manufacture, software like Excel or Matlab etc based on the linear programming, and the some intelligent method like genetic algorithm and Neural network. For the optimization of granulation process, a novel way named Moisture Capacity was proposed by Lv et al., which aimed to solve the problem of the specifying of water content. For the prediction of the sinter quality and sinter plant performance indices, H.Saxen et al. set up a model of neural network.; For the process of blast furnace, Wu et al. described the mathematical model for blast furnace burden optimization based on the high-temperature reactivity. On the other hand, the neural network, the genetic algorithm and decision support system (DSS) were widely used in iron-making, A.Agarwal, U.Tewary et al. tried to analyze blast furnace data by using evolutionary neural network and multi-objective genetic algorithms, which constructed for productivity, CO2 content of the top gas and Si content of the hot metal. A considerable amount of studies had been reported, which referred to the behavior and performance of single ore at one step of the iron-making process; however, the evaluation of mixed ore in the whole iron-making process was less reported. The reasons were as follows: the steel plants paid more attention on the benefits and less consideration on the fundamental and systematic studies; secondly, there was certainly in defect of a feasible method to evaluate the whole complex process.
According to the mentions above, the present study tried to develop an evaluation system, which could optimize the process parameters and predict the economic and technical indices in the whole iron-making process.

2 DESIGNING AND REALIZATION OF THE EVALUATION SYSTEM

2.1 Primary Idea

The primary idea of the evaluation system is as follows: first, the iron-making process is divided into five units according to their relative independence; second, the economic and technical indices are specified in each unit, then performance and effect of iron ore in the system is calculated quantitatively and shown in a monetary form; third, a connection model is built on the interface of units to link the technical variable in former unit and the technical and economic variable in latter unit; at last, an ultimate economic index is given by aggregating all economic indices at every unit.

ISSN 2176-3135

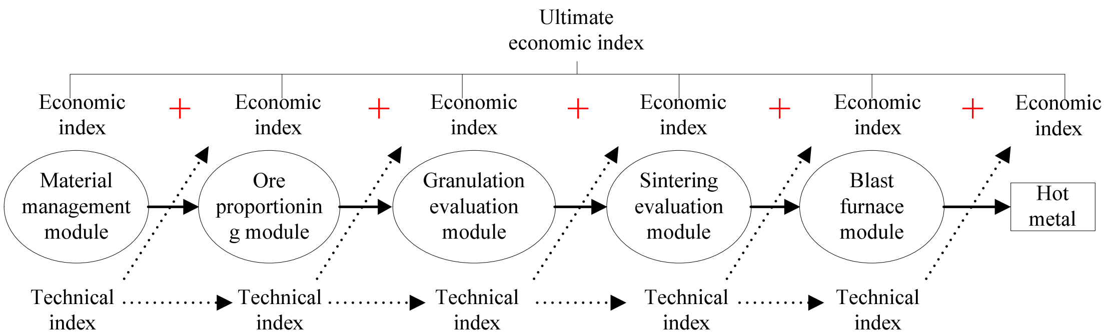

Figure 1. Flow chart of evaluation system for iron-making.

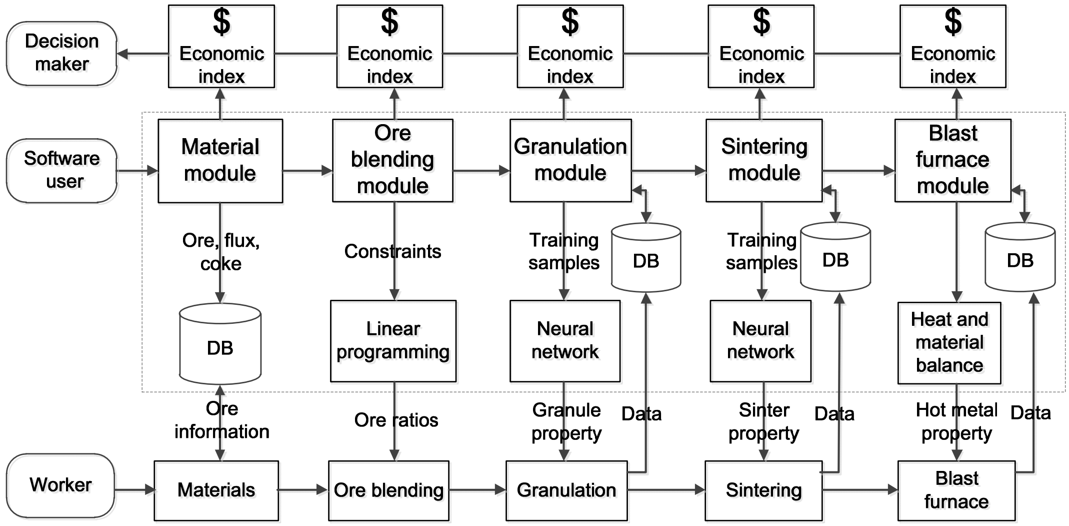

Figure 2. Structure of iron-making evaluation system.

Figure 1 shows the design idea. The advantages of the system are: i) Integrity, the iron-making process from ore to hot metal is thought of as a whole and there is the information of parameters and feedback controls transferred among units. ii) Self-learning ability, the expert knowledge database formed by the system is scalable and portable. With the increase of data collection and storage, the stability and accuracy will become better and better.
Figure 2 shows the structure of the evaluation system. According to the distribution of information, the system has a hierarchical architecture on three layers: physical layer, model layer and decision layer. The system can meet the different desires of data and information for the various users.

2.3 Realization of Evaluation System

2.3.1 Model of raw material management

The species of ores used in the iron-making process are various and complex, it is out of the capability of traditional models for managing materials adequately. In order to dispatch and utilize iron ores effectively, a novel model of raw material management is built. This model is composed of ore information database and ore physiochemical database. The ore information database includes ore resource information (producing place, price, transport cost, storage, and storage time etc.), mineral type, thermal analysis, and moisture capacity; ore physiochemical database includes chemical constitution, surface features (porosity, specific surface area, XRD, and SEM), particle size, and density (true density and bulk density), as shown in Table1.

ISSN 2176-3135

Table 1. Model of raw material management

Ore physiochemical database				Ore information database			
Chemical constitution	Surface features	Grain size	Density	Resource information	Mineral type	Thermal Analysis	Moisture capacity

2.3.2 Model of ore proportioning by linear programming

The core algorithm is simple method in the model, the function is to calculate the suitable ores mix scheme and property of mixture.[2,5]

i) Objective function

$$Min\ C = \sum_{i=1}^{n} c_i \times p_i$$

Where: *Min C* represents optimal cost of per ton sinter (yuan), c_i represents unit price of material *i* (yuan/ton), p_i represents percentage of material *i*.

ii) Constraints of chemical constitution

$$l_j \le \frac{\sum_{i=1}^{n} p_i \times a_{ij} \times (1 - H_i)}{\sum_{i=1}^{n} p_i \times a_{ij} \times (1 - H_i) \times (1 - L_i)} \le u_j$$

Where: a_{ij} represents percentage of element *j* of material *i*, H_i represents percentage of H_2O of material *i*, L_i represents percentage of melting loss of material *i*, u_j represents upper boundary of composition *j* of sinter, l_j represents lower boundary of composition *j* of sinter.

iii) Constraints of particle size of sinter mixture

$$l_j \le \sum_{i=1}^{n} p_i g_{ij} \le u_j$$

Where: g_{ij} represents percentage of particle size *j* of material *i*.

iv) Constraints of material compositions of sinter mixture

$$P_{li} \le p_i \le P_{ui}$$

Where P_{ui} represents upper boundary of material *i*, P_{li} represents lower boundary of material *i*.

2.3.3 Model for the iron ore granulating

The model consists of two sub models: the optimization model of granulating parameter and the prediction model of granule property.

It is evident that the water content and permeability of the mixture play an important role in granule property and performance. How to determine the water content and predict the permeability of the mixture is still a problem. First, the suitable water content could be gotten by the application of moisture capacity[9,10] in the optimization model of granulating parameter; second, the permeability and other properties of granules could be also gotten by the neural network in the prediction model of granule property.

2.3.3.1 Determination of moisture capacity

Moisture capacity, is defined as the maximum water content held in the iron ore particles of unit mass, and reflects the hydrophilic ability of material. As a comprehensive concept, moisture capacity is determined by chemical constitution, particle size and morphology, porosity, and specific surface area, etc.

ISSN 2176-3135

$$\gamma_g = \frac{Ms - M}{M} \times 100\%$$

Where: γ_g is the dry based moisture capacity, *Ms* is the mass of water saturated material; *M* is the mass of dry material.

2.3.3.2 Estimation of on strand permeability

The on strand permeability is a variable that must be reconstructed from indirect information. The gas flow resistance of the sinter strand is essentially that of a fixed bed, so it would be possible to approximate the gas pressure drop Δp_{bed} over the bed by the Ergun equation

$$\frac{\Delta p_{bed}}{h} = 150 \frac{1-\varepsilon^2}{d_p^2 \varepsilon^2} \mu u_0 + 1.75 \frac{1-\varepsilon}{d_p \varepsilon^3} \rho u_0^2$$

Where: *h* is the bed height, ε is the porosity of the bed, d_p is the diameter of the particles, μ is the viscosity, u_0 is the superficial velocity and ρ is the density of the gas.

2.3.3.3 Optimization model of granulating parameter

The task of the model is to deduce a suitable water amount from the application of moisture capacity with the assumption that equipment and operation parameters are constants. The equation can be expressed as:

$$Mo = 0.12 \times \gamma_g + 6.94$$

Where: Mo is the suitable water amount for sinter mixture.

2.3.3.4 Prediction Model of granule property

The model is based on the BP neural network, the inputs and outputs of the model are shown in Figure 3. The analysis was based on 48 groups data from experiments, because there was in defect of factory data. What the model different from traditional ones(11-14) is the introduction of moisture capacity. Since introducing of moisture capacity, generalization ability and accuracy of the model is greatly enhanced, and the model result doesn't sharply fluctuate with the changing of ore type, the producing place, weather, or storage time.

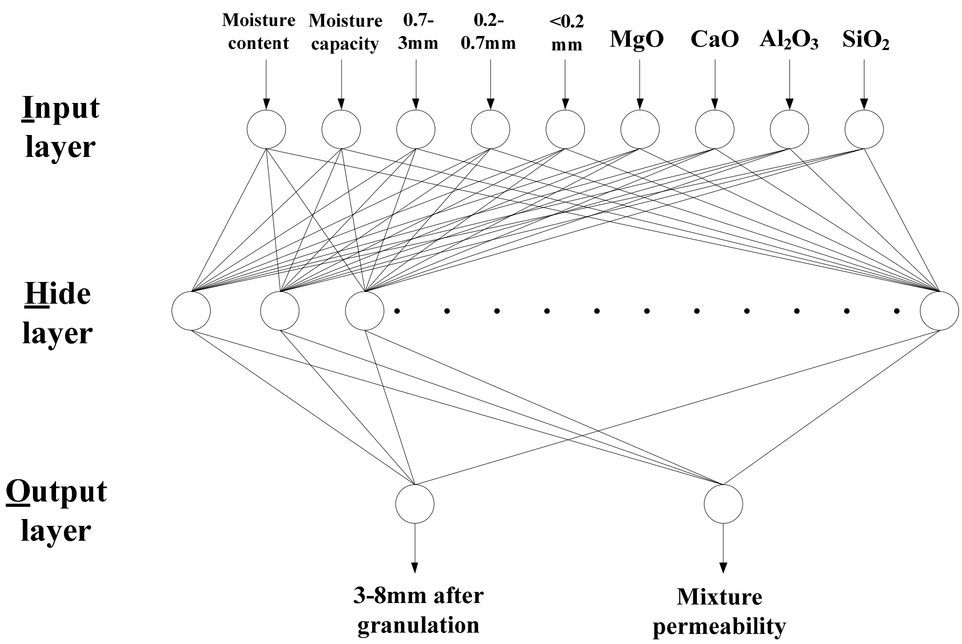

Figure 3. BP neural network of the prediction model of granule property.

ISSN 2176-3135

2.3.4 Model for the iron ore sintering

Model for the iron ore sintering also consists of two sub models: the optimization model of sintering parameter and prediction model of sinter property.

2.3.4.1 Optimization Model of sintering parameter

The task is to find out a suitable coke proportion for sintering by mass and heat balancing calculation under the assumption that equipment and operation parameters are constants in sintering process.

2.3.4.2 Prediction Model of sinter property

The model is based on BP neural network,[15-18] and the data set was based on historical data from a two year period of a Chinese sinter plant, with values from totally 693 days. For the sake of detecting the most relevant inputs from a large set of potential ones, an exhaustive search was undertaken by orthogonal design and sinter pot experiment. Firstly, an orthogonal table on all potential triples of input variables was selected; secondly, the sinter pot experiment was carried out; thirdly, the experiment result was treated by range analysis and high relevant inputs were selected out; finally, the experiment results, which were used for training and prediction of neural network, were stored in the database. In addition, the production amount of liquid and calorific effect in sintering was calculated by FactSage v6.3; moreover, the calculation result was certificated by slag melting performance tester, high-temperature XRD analysis, mineralogical microscopic analysis, and synchronous thermal analyzer; at last, the certificated result was taken as training samples for the prediction model of sinter property, as shown in Figure 4.

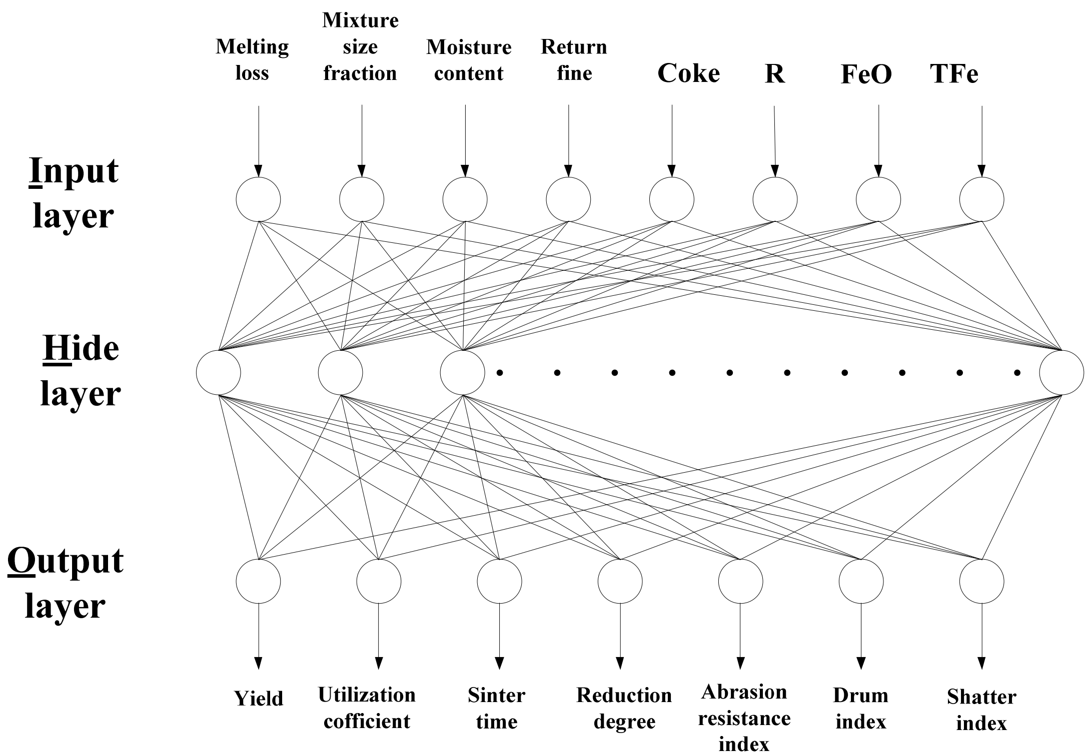

Figure 4. BP neural network of the prediction model of sinter property.

2.3.5 Model of blast furnace

As the most important model in the evaluation system for iron-making process, the functions of the model of blast furnace are as follows: energy saving, consumption

ISSN 2176-3135

reduction, and improving burden structure for blast furnace. The model is formed of two sub models: the model of burden management and the prediction model of quality of hot metal.

2.3.5.1 Model of burden management

This model contains a material database including iron bearing materials (sinter ore, lump ore, and pellet), fuel (coke and coal), and fluxes.

2.3.5.2 Prediction model of quality of hot metal

The task of this model is to predict chemical constitution of hot metal and slag, degree of direction reduction, coke rate and ore consumption, on the basis of heat and material balance calculation.

3 DEVELOPMENT AND APPLICATION OF THE EVALUATION SYSTEM

The software for the evaluation system is compiled by C# and MySql database, and widely used in iron-making process. The software was applied in certain iron and steel enterprise. Table 2. Data from software and industry

		By software	Industrial data
Granulating	Water content/%	5.91	9
	3-8mm/%	69.6	46.4
	3-5mm/%	20.8	26.7
	Mixture permeability/mmH_2O	221.1	345.08
Sintering	Shatter index/%	68.2	56.91
	Drum index/%	59.6	78.29
	Abrasion index/%	3.7	3.685
	Sintering speed/mm·min^{-1}	18.2	19.28
	Yield/%	89.1	89.61
Blast furnace	Coke ratio/kg·t^{-1}	374	376
	Direct-reduction degree/%	58	
Economical indices	BF/yuan·t^{-1}	2429.33	2350
	Ore consumption	1.809	1.668

shows the data calculated by software and iron-making industry.

Table 2. Data from software and industry

		By software	Industrial data
Granulating	Water content/%	5.91	9
	3-8mm/%	69.6	46.4
	3-5mm/%	20.8	26.7
	Mixture permeability/mmH_2O	221.1	345.08
Sintering	Shatter index/%	68.2	56.91
	Drum index/%	59.6	78.29
	Abrasion index/%	3.7	3.685
	Sintering speed/mm·min^{-1}	18.2	19.28
	Yield/%	89.1	89.61
Blast furnace	Coke ratio/kg·t^{-1}	374	376
	Direct-reduction degree/%	58	
Economical indices	BF/yuan·t^{-1}	2429.33	2350
	Ore consumption	1.809	1.668

From the table, we can see that:

ISSN 2176-3135

- In granulating, the data generated by software was better. The water content was less and the amount of 3-8mm granules was more, which led to the mixture permeability better.
- In sintering, the data by software, such as drum index, abrasion index and sintering speed, was decreased; however, the yield of sinter ore was nearly equal to each other.
- In blast furnace and economical evaluation, the industrial data owns a better performance in ore consumption and cost in blast furnace. However, the scheme used in software utilized more domestic ores of low grade, which achieves the reasonable utilization of imported ore and domestic ore and minimizes the cost on the premise of properties.

ISSN 2176-3135

4 CONCLUSIONS

- The evaluation system for iron-making process, which is consist of material management module, ore proportioning module, granulating evaluation module, sintering evaluation module and blast furnace evaluation module, was built and applied to the iron-making process. The results indicated that this system can respectively give the cost of a series of intermediate products and technical parameters and carry out the full flow iron-making economic and technical evaluation, so that the utilization efficiency of multiple ores can be improved.
- according to the distribution of information in modern iron enterprise, the evaluation system for iron-making process has a hierarchical structure organized on three layers: physics layer, model layer, and decision layer, which can realize optimization and hierarchical management on information resources.
- iron-making evaluation software is designed and developed by C# and MySql database and has been used in some plants.

Acknowledgments

The authors are gratefully gratitude to the Fundamental Research Funds for the Central Universities for the financial support (No.CDJRC CDJZR11130002).

REFERENCES

1 DAI, S.-h., SHEN, F.-m., CHU, M.-s., & YU, A.-b. Comparison among size prediction models for granulation of iron-bearing materials. Journal of Materials and Metallurgy 2006, 5, 3-13.
2 LU, X., BAI, C., Qiu, G., & HUANG, Q. Research on Methods of Solution to Model of Sintering Burdening Optimization. Journal of Basic Science and Engineering 2008, 16, 695-702.
3 Nath, N., & Mitra, K. Mathematical Modeling and Optimization of Two-Layer Sintering Process for Sinter Quality and Fuel Efficiency Using Genetic Algorithm. Materials and Manufacturing Processes 2005, 20, 335-349.
4 Ono, H., Dohi, Y., Arikata, Y., & Usui, T. Effect of mineral composition and pore structure on reducibility of composite iron ore sinter. ISIJ International 2009, 49, 722-728.
5 QIN, L., LI, Y.-f., & LI, Z. Optimization of Sintering Blending Based on Adaptive Evolutionary Algorithm. Industry and Mine Automation 2011, 67-70.
6 WANG, Y.-F., Wu, S., & HAN, H.-I. Improvement in quality indices of sinter with high proportion of limonite. Journal of University of Science and Technology Beijing 2010, 32, 292-297.
7 Wu, S., Han, H., & Liu, X. Mathematical Model for Blast Furnace Burden Optimization Based on the High-temperature Reactivity. ISIJ International 2010, 50, 987-993.
8 Zhang, R., Lu, J., & Zhang, G. A knowledge-based multi-role decision support system for ore blending cost optimization of blast furnaces. European Journal of Operational Research 2011.
9 Lv, X., Bai, C., Qiu, G., Zhang, S., & Hu, M. Moisture Capacity: Definition, Measurement, and Application in Determining the Optimal Water Content in Granulating. ISIJ International 2010, 50, 695-701.
10 Lv, X., Bai, C., Qiu, G., Zhang, S., & Shi, R. A Novel Method for Quantifying the Composition of Mineralogical Phase in Iron Ore Sinter. ISIJ International 2009, 49, 703-708.

ISSN 2176-3135

11 Sakamoto, N. Iron ore granulation model supposing the granulation probability estimated from both properties of the ores and their size distributions. ISIJ International 2002, 42, 834-843.
12 SUN, L., & JIN, W. Neural network applied in moisture control for sinter mixture. Journal of Dalian Institute of Light Industry 2003, 22, 211-213.
13 Venkataramana, R., Kapur, P., & Gupta, S. Modelling of granulation by a two-stage auto-layering mechanism in continuous industrial drums. Chemical engineering science 2002, 57, 1685-1693.
14 Waters, A., Litster, J., & Nicol, S. A mathematical model for the prediction of granule size distribution for multicomponent sinter feed. ISIJ Int. 1989, 29, 274-283.
15 Laitinen, P. J., & Saxén, H. A neural network based model of sinter quality and sinter plant performance indices. Ironmaking & Steelmaking 2007, 34, 109-114.
16 LONG, H., FAN, X., & CHEN, X. Expert system for controlling sinter chemistry based on neural network prediction. Journal of University of Science and Technology Beijing 2006, 28, 867-870.
17 Mukherjee, M., & Singh, S. B. Artificial Neural Network: Some Applications in Physical Metallurgy of Steels. Materials and Manufacturing Processes 2009, 24, 198-208.
18 TITAN, W.-h. Optimization Expert System for Sintering Proportion. Sintering and Pelletizing 2006, 31, 23-26.