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Qualitative and Quantitative Synthetic Methodology for Blending Optimization in Lead-zinc Sintering ⋆

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Abstract: To deal with the problem of high cost and low accuracy existed in conventional methods for the lead-zinc sintering blending, a qualitative and quantitative synthetic methodology for sintering blending optimization is presented in this paper. First, two prediction models are built based on a process neural network and the improved grey system theory. Next, these two models are integrated into one prediction model by using the concept of entropy. It guarantees the prediction precision of the Pb and Zn components in the agglomerate. Then, a blending optimization model is established to minimize the costs. Finally, the component ratios are optimized by using the expert reasoning strategy and an integrated synthesis methodology.

1. INTRODUCTION

The imperial smelting process (ISP) in lead-zinc metallurgy, which involves sintering and smelting, produces agglomerate with prescribed mechanical strength, porosity and reducibility [Du, 2004]. As a material preparatory process for reduction smelting, the lead-zinc sintering process (LZSP) plays an important role in the ISP. The blending process is the first operation in the working procedure of the sintering process. It contains two steps: the primary and secondary proportioning. The ratios of some chemical components of blended material are key parameters in the LZSP [Gui, 2007]. They give big influence on sintering permeability and other parameters. As a result, they affect the quantity and quality (Q&Q) of the agglomerate. So, it is very important to control those ratios of the chemical components in the blended material.

Recently, the optimization problem of the LZSP has been attracting a great deal of attention. However, studies have mainly focused on the optimization and control for the state parameters and performance indices, such as permeability, burning through point and Q&Q [Chen, 2003, Wu, 2006]; few attempts on the blending process have been investigated. As a result, in most cases, the ratios of chemical components are determined by the conventional checking method, and are calculated by operators. This method has some drawbacks. First, the production cost and the quality of the agglomerate are not directly considered in the determination of the ratios. Second, it is difficult to detect the chemical components of the agglomerate timely and used them to perform the ratio control of the agglomerate. So, this method causes high cost and low accuracy of the sintering blending process. It is urgent how to determine optimal ratios and reduce the production cost under prescribed technological requirements of the agglomerate quality.

Along with the progress of the artificial intelligence, some intelligent control and optimization methods have been applied to the optimization and control of the blending process involved in many production processes [Glismann, 2001, Cierpisz, 2002]. In particular, a model-based expert control strategy using neural networks (NNs) was presented for the control of the coal blending process in an iron and steel plant [Wu, 1999], it was implemented in an expert control system that contains an expert controller and a distributed controller. A new type of the Takagi-Sugeno fuzzy controller based on an incremental algorithm was reported for the cement raw material blending process [Bavdaz, 2007]. A coal-blending model has been developed by employing the relationship between the quality parameters of coal and coke [Gupta, 2007], it reduced the cost a great deal under the guarantee of the quality of blended coal. These motivated us to investigate the optimization and control problem of the lead-zinc sintering blending process.

In this paper, an integrated prediction model for the chemical components of agglomerate and an optimization model of the blending process are established. Based on the mechanism analysis of the LZSP, an expert reasoning strategy is presented. Optimization of the sintering blending process is carried out from the systematic viewpoint by using the Q&Q synthetic methodology [Yu, 2000]; which combines the technology of process NN (PNN), the improved grey system theory (IGST), and the expert reasoning method. Optimal ratios of the chemical components in the agglomerate are obtained by using the presented methods. The results of real-world applications show that the precision

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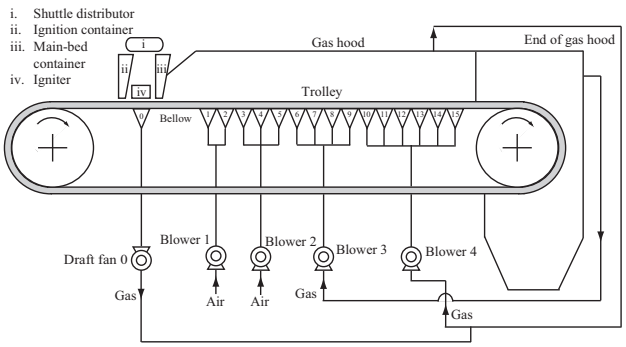

Fig. 1. Dwight-Lioyd sintering machine

of the integrated prediction model is higher than that of a PNN prediction model or an IGST-based prediction model.

2. MECHANISM ANALYSIS FOR LEAD-ZINC SINTERING PROCESS

The blast sintering process considered in this study is carried out in a Dwight-Lioyd (DL) type sintering machine, which has five blowers: Draft fan 0 is used for ignition, Blower 1 and Blower 2 send fresh gas, and Blower 3 and Blower 4 send returned gas, as shown in Fig. 1.

After the material is proportioned, it is then blended, granulated, and finally becomes blended balls with appropriate water content. These balls are sent to ignition container and main-bed container by a shuttle distribution. Those balls are poured into the trolley to a depth of 3 cm to form a bed called ignition layer and are ignited by the igniter.

Ignition temperature is controlled to ignite the blending material on the ignition layer by means of gas flux. The trolley propels the blending materials along. Once the ignition layer is burning, more balls are added on top to form a bed 30∼40 cm thick. The blended balls is moved by trolley. After four phases (evaporation, heating, reaction, sintering), the blended balls become a sintering agglomerate with a certain structure, and are discharged from the back of the sintering machine. Qualified sintering agglomeration are sent to the smelting process while others are returned through two-level fragmentation and cooling process to produce returned powder.

The lead-zinc sintering process is a complicated physical and chemical reaction process with strong nonlinearity, a large time delay, and time-varying parameters. It takes about 2 hours from the beginning of blending to the end of sintering, and the variables are only detected once in one process. So, it makes the detected data of the chemical components of the agglomerate cannot be used in a real-time control system. And an effective prediction model for the chemical components of the agglomerate needs to be built. At the same time, the component ratios of the blended material have also to be optimized because the exact ratios of the components in the blended material is the most important factor that affects the quality of agglomerate and the production cost.

3. INTEGRATED PREDICTION MODEL OF AGGLOMERATE COMPONENT

3.1 PNN Prediction Model

The effect of $x_{k-1}, x_{k-2}, \cdots$ on x_k is apparently hard to express when the conventional artificial neural network [Frank, 2001] is used to predict the agglomerate components, x_{k+1}, at the time $k+1$; or in other words, it is difficult to express the temporal accumulation in time series. This certainly affects the prediction accuracy.

This can be regarded as a nonlinear mapping between x_{k+1} and x_k, i.e.,

$$x_{k+1} = F(x_k(t)). \tag{1}$$

Then, the problem of prediction for the agglomerate components in the time axis can be transformed to an approximation to the function $F(\cdot)$. It is known that a PNN can be used to approximate a random continuous function [He, 2000]. So, we can set $x_k(t)$ to be the input of a PNN, and find a PNN to approximate the function $F(\cdot)$.

The PNN-based time series prediction model for the lead-zinc agglomerate components presented in this paper is a three-layer forward PNN whose topology structure is 1-10-1. Let $x(t) = x_k(t)$, the prediction value of the components at $k+1$ is

$$\hat{y} = \sum_{i=1}^{10} v_i f\left(\int_0^T w_i(t)x(t)dt - \theta_i\right) - \theta, \tag{2}$$

where $x(t)$ is the input of the process neurons; $[0, T]$ is the sampling interval; $w_i(t)$ and v_i are the connecting weights from the input layer to the hidden layer and from the hidden layer to the output layer, respectively; θ is a threshold of the PNN; $f(\cdot)$ is the prompting function.

According to the Weierstrass approaching theorem, a group of standard orthogonal basis function $b_j(t)$ $(j = 1, 2, \cdots, J)$ in the space of $[0, T]$ is acquired by taking the Gram-Schmidt orthogonal steps. Then, $x(t)$ and $w_i(t)$ are expressed to be

$$x(t) = \sum_{j=1}^{J} a_j b_j(t), w_i(t) = \sum_{j=1}^{J} w_{ij} b_j(t), \tag{3}$$

where a_j and $w_{ij} \in R$ are coefficients of the expansion equation. According to the characteristics of the orthogonal function, (3) is simplified to be

$$\hat{y} = \sum_{i=1}^{10} v_i f\left(\sum_{j=1}^{J} w_{ij} a_j - \theta_i\right) - \theta. \tag{4}$$

For given L pair of learning samples $\{x_l(t), d_l\}$ $(l = 1, 2, \cdots, L)$, where $x_l(t)$ and d_l are the input and expected output of the network, respectively; if $\hat{y}_l$ is the corresponding output, then the error function of the model is defined to be

$$E = \frac{1}{2}\sum_{l=1}^{L}(\hat{y}_l - d_l)^2 = \frac{1}{2}\sum_{l=1}^{L}\left(\sum_{i=1}^{10} v_i f\left(\sum_{j=1}^{J} w_{ij}a_{jl} - \theta_i\right) - \theta - d_l\right)^2. \quad (5)$$

Denote $Z_{il} = \sum_{j=1}^{J} w_{ij}a_{jl} - \theta_i$. According to the rapid stochastic gradient descent algorithm, adjusting rules for training parameters of the model are

$$\begin{cases} v_i(s+1) = v_i(s) + \alpha\Delta v_i(s), \\ w_{ij}(s+1) = w_{ij}(s) + \beta\Delta w_{ij}(s), \\ \theta_i(s+1) = \theta_i(s) + \gamma\Delta\theta_i(s), \\ \theta(s+1) = \theta(s) + \delta\Delta\theta(s), \end{cases} \quad (6)$$

where α, β, γ and δ are parameters of the learning velocity; s is the iteration number of learning. In each learning iteration, Δv_i,Δw_{ij},$\Delta\theta_i$ and $\Delta\theta$ are given by

$$\begin{cases} \Delta v_i = -\dfrac{\partial E}{\partial v_i} = -\sum_{l=1}^{L}(\hat{y}_l - d_l)f(Z_{il}), \\ \Delta w_{ij} = -\dfrac{\partial E}{\partial w_{ij}} = -\sum_{l=1}^{L}(\hat{y}_l - d_l)v_i f'(Z_{il})\alpha_{jl}, \\ \Delta\theta_i = -\dfrac{\partial E}{\partial \theta_i} = \sum_{l=1}^{L}(\hat{y}_l - d_l)v_i f'(Z_{il}), \\ \Delta\theta = -\dfrac{\partial E}{\partial \theta} = \sum_{l=1}^{L}(\hat{y}_l - d_l). \end{cases} \quad (7)$$

The learning steps are

Step 1. Represent the input function and weights of the PNN model as basis functions using the Legendre orthogonal basis function.
Step 2. Let the number of learning iteration $s = 0$; and choose the biggest number of learning iteration, D; the allowable learning error, ϵ; and the parameters α, β, γ and δ.
Step 3. Set the initial values of the weights and threshold to be zero.
Step 4. Calculate the error function, E, using to (5). If $E < \epsilon$ or $s > D$, then go to Step 6 and finish. Otherwise go to Step 5.
Step 5. Adjust the weights and threshold according to (6) and (7), let $s + 1 \to s$, and go to Step 4.
Step 6. Output the learning results.

3.2 IGST-based Prediction Model

Assume that the original data sequence of the agglomerate components is $Y^{(0)} = \{y^{(0)}(1), y^{(0)}(2), \cdots, y^{(0)}(n)\}$. When the grey system model [Yao, 2003, Lin, 2007] is employed to predict the agglomerate component, the prediction result is not very accurate if the original data fluctuates. In order to reduce the influence of the fluctuates and improve the prediction precision, the exponential smoothing method is adopted in this paper. In particular,

$$y^*(k) = 0.5y(k) + 0.5y(k-1)$$

was used in this study. After the smoothing operation, we can obtain a sequence $Y^{(0)*}$. Then, the sequence $Y^{(1)}$ is formed by applying the accumulated generating operation (AGO) technique to the sequence $Y^{(0)*}$.

$$\begin{cases} Y^{(1)} = \{y^{(1)}(1), y^{(1)}(2), \cdots, y^{(1)}(n)\}, \\ y^{(1)}(k) = \sum_{i=1}^{k} y^{(0)*}(i). \end{cases} \quad (8)$$

The following first order difference equation is established

$$\frac{dy^{(1)}}{dt} + ay^{(1)} = b, \quad (9)$$

where a is a development coefficient, which reflects the development trend of the original data sequence $Y^{(0)}$ and the first order accumulated generating operation sequence $Y^{(1)}$. b is the grey input, which reflects the variation of the data.

Let $A = [a, b]^T$, the method of least squares is used to yield it:

$$A = (B^T B)^{-1} B^T X_N, \quad (10)$$

$$B = \begin{bmatrix} -0.5(y^{(1)}(1) + y^{(1)}(2)) & 1 \\ -0.5(y^{(1)}(2) + y^{(1)}(3)) & 1 \\ -0.5(y^{(1)}(3) + y^{(1)}(4)) & 1 \\ \vdots & \vdots \\ -0.5(y^{(1)}(n-1) + y^{(1)}(n)) & 1 \end{bmatrix},$$

$$X_N = \left[\, y^{(0)}(2)\ y^{(0)}(3)\ y^{(0)}(4)\ \cdots\ y^{(0)}(n) \,\right]^T.$$

The grey system model GM(1, 1) is obtained by substituting a and b into (9) and solving

$$y^{(1)}(k+1) = \left[y^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a},\ k = 0, 1, 2, \cdots. \quad (11)$$

Applying the inverse AGO to the (11), we obtain the grey prediction model of the original sequence $Y^{(0)}$ of the agglomerate component:

$$\hat{y}^{(0)}(k) = \hat{y}^{(1)}(k) - \hat{y}^{(1)}(k-1), k = 1, 2, \cdots. \quad (12)$$

3.3 Entropy-Based Integrated Prediction Model

In order to improve the prediction precision, we integrated the above two models. The integrated prediction model is established and the optimal weights are determined by using the entropy method.

Assume that, the number of prediction models employed is I, $\{y_t, t = 1, 2, \cdots, M\}$ is the actual value of the agglomerate components in time series, and $\hat{y}_{it}$ is the prediction value of the i-th prediction model at time t. Then $E_{it} = |y_t - \hat{y}_{it}|$ is defined as the absolute value of the prediction error of the i-th prediction model at time t. Then the prediction value of the integrated prediction model is:

$$\hat{y}_t = \sum_{i=1}^{I} w_i \hat{y}_{it}, i = 1, 2, \cdots, I, t = 1, 2, \cdots, M, \quad (13)$$

where w_i is the weight of the i-th prediction model, and satisfies

$$\sum_{i=1}^{I} w_i = 1, w_i \geq 0, i = 1, \cdots, I. \quad (14)$$

In this paper, we set $I = 2$.

Assume that $\hat{y}_{it}$ is the prediction value of the i-th model at the time t. Let

$$e_{it} = \begin{cases} \left|\dfrac{y_t - \hat{y}_{it}}{y_t}\right|, \text{ if } 0 \le \left|\dfrac{y_t - \hat{y}_{it}}{y_t}\right| < 1; \\ 1, \qquad\quad \text{if } \left|\dfrac{y_t - \hat{y}_{it}}{y_t}\right| \ge 1. \end{cases} \tag{15}$$

Then e_{it} denotes the relative prediction error of the i-th prediction model at time t. Note that $0 \le e_{it} \le 1$ $(i = 1, 2, \cdots, I; t = 1, 2, \cdots, M)$; and $\{e_{it}\}$ is the relative prediction error series of the i-th prediction model at time t.

The mutation degree of the prediction error series of the i-th prediction model is redefined by employing the concept of the information entropy in this paper [Themis, 2005, Mohaned, 2007]. The steps for determining the weights are as follows.

Step 1. Calculate the relative prediction error, p_{it}, of the i-th prediction model at time t:

$$p_{it} = \frac{e_{it}}{\sum_{t=1}^{M} e_{it}}, i = 1, \cdots, I; t = 1, \cdots, M. \tag{16}$$

Step 2. Calculate the entropy of the relative prediction error, E_i, of the i-th prediction model:

$$E_i = -r \sum_{t=1}^{M} p_{it} \ln p_{it}. \tag{17}$$

where $r > 0$ ($r = 1/\ln M$ was used in this paper).

Step 3. Calculate the mutation degree coefficient, d_i, of the relative prediction error series of the i-th prediction model as follows. Since the entropy of the relative prediction error is the reverse of its mutation degree, d_i is given by

$$d_i = 1 - E_i, i = 1, \cdots, I. \tag{18}$$

Step 4. Calculate the weight w_i:

$$w_i = \frac{1}{I-1}\left(1 - \frac{d_i}{\sum_{i=1}^{I} d_i}\right) \tag{19}$$

Step 5. Calculate the prediction value $\hat{y}_t$ of the integrated prediction model.

$$\hat{y}_t = \sum_{i=1}^{I} w_i \hat{y}_{it}, t = 1, 2, \cdots, M. \tag{20}$$

4. OPTIMIZATION METHOD FOR SINTERING BLENDING

4.1 Blending Optimization

The blending process contains the primary and secondary proportioning. In the primary proportioning, different kinds of lead-zinc ore are blended according to prescribed ratios to produce a mixture. This step adjusts the ratios of Pb, Zn and SiO_2 in the blended material. In order to make the agglomerate component meet the requirement of the smelting production, and to reduce the cost of raw material, an optimal primary proportioning model, which minimizes cost under the constraints of agglomerate components, is as follows.

$$\min f(x) = \min \sum_{i=1}^{N} C_i x_i \tag{21}$$

$$\text{s.t.} \begin{cases} [\mathrm{Pb}]^g_{C\min} \le [\mathrm{Pb}]_C = \sum_{i=1}^{N} x_i [\mathrm{Pb}]_i \le [\mathrm{Pb}]^g_{C\max} \\ [\mathrm{Zn}]^g_{C\min} \le [\mathrm{Zn}]_C = \sum_{i=1}^{N} x_i [\mathrm{Zn}]_i \le [\mathrm{Zn}]^g_{C\max} \\ [\mathrm{S}]^g_{C\min} \le [\mathrm{S}]_C = \sum_{i=1}^{N} x_i [\mathrm{S}]_i \le [\mathrm{S}]^g_{C\max} \\ [\mathrm{CaO}]^g_{C\min} \le [\mathrm{CaO}]_C = \sum_{i=1}^{N} x_i [\mathrm{CaO}]_i \le [\mathrm{CaO}]^g_{C\max} \\ \frac{1}{1.7}[\mathrm{CaO}]_C \le [\mathrm{SiO_2}]_C = \sum_{i=1}^{N} x_i [\mathrm{SiO_2}]_i \le \frac{1}{1.4}[\mathrm{CaO}]_C \\ [Fe]_C = \sum_{i=1}^{N} x_i [Fe]_i > 2[\mathrm{SiO_2}]_C \end{cases}$$

where C_i is the cost price of the i-th lead-zinc ore, $[\mathrm{A}]^g_{C\max}$ and $[\mathrm{A}]^g_{C\min}$ are the upper and lower ratio indexes of the component A in the blended material, respectively. They are determined by the quality requirement of the agglomerate. For example, consider the component Pb. The relationship between its ratios in the blended material component and the agglomerate is

$$[\mathrm{Pb}]_M = w[\mathrm{Pb}]_C + (1-w)[\mathrm{Pb}]_R, \tag{22}$$

$$[\mathrm{Pb}]_S = f_{PNN+IGST}(X), \tag{23}$$

where w ($\in [0, 1]$) is the ratio of Pb in the blended material for the secondary proportioning. The relationship between the component in the blended material of the primary and secondary proportioning is shown in (22). $f_{PNN+IGST}(X)$ denotes the integrated prediction model of the component in the agglomerate. The subscripts M, C and R denote the blended material of the secondary proportioning, the blended material of the primary proportioning and the returned powder, respectively.

4.2 Optimization of Ratios

On the basis of the above optimal model, according to the following steps, the component ratios in the blended material of the primary proportioning are determined by an expert reasoning strategy as follows.

Step 1. Calculate the component index $[\mathrm{A}]^g_{C\max}$ and $[\mathrm{A}]^g_{C\min}$ of the blended material. They are calculated according to the requirement of the agglomerate component index and by retro-reasoning of the expert reasoning. For example, Consider Pb component index of the blended material. Suppose that $[\mathrm{Pb}]^g_{M\max}$ and $[\mathrm{Pb}]^g_{M\min}$ are the Pb component index of the blended material educed from the integrated prediction model of the agglomerate component based on (23) using the rules such as $R_1 \sim R_4$.

R_1: If $[\mathrm{Pb}]_S > [\mathrm{Pb}]^g_{S\max}$ and $[\mathrm{S}]_M$ are big, then decrease $[\mathrm{Pb}]_M$.

R_2: If $[\mathrm{Pb}]_S < [\mathrm{Pb}]^g_{S\min}$ and $[\mathrm{S}]_M$ are big, then increase $[\mathrm{Pb}]_M$ and decrease $[\mathrm{S}]_M$.

R_3: If $[\mathrm{Zn}]_S > [\mathrm{Zn}]^g_{S\min}$ and $[\mathrm{S}]_M$ are small, then decrease $[\mathrm{Zn}]_M$ and increase $[\mathrm{S}]_M$.

R_4: If $[\mathrm{Zn}]_S < [\mathrm{Zn}]^g_{S\min}$ and $[\mathrm{S}]_M$ are big, then increase $[\mathrm{Zn}]_M$ and decrease $[\mathrm{S}]_M$.

According to the (22), we have

$$[\mathrm{Pb}]_C = \frac{[\mathrm{Pb}]_M - (1-w)[\mathrm{Pb}]_R}{w}. \tag{24}$$

According to the optimal bounds $[w_{\min}, w_{\max}]$ of the secondary proportioning, we have

$$[\mathrm{Pb}]^g_{C\max} = \max\left\{\frac{[\mathrm{Pb}]^g_{M\max} - (1-w_{\min})[\mathrm{Pb}]_R}{w_{\max}}, \frac{[\mathrm{Pb}]^g_{M\max} - (1-w_{\min})[\mathrm{Pb}]_R}{w_{\min}}\right\}, \tag{25}$$

$$[\mathrm{Pb}]^g_{C\min} = \min\left\{\frac{[\mathrm{Pb}]^g_{M\min} - (1-w_{\max})[\mathrm{Pb}]_R}{w_{\max}}, \frac{[\mathrm{Pb}]^g_{M\min} - (1-w_{\min})[\mathrm{Pb}]_R}{w_{\min}}\right\}. \tag{26}$$

Step 2. Choose the initial values of x_i $(i = 1, \cdots, N)$ from the knowledge base.

Step 3. Calculate $[\mathrm{A}]_C$ based on the selected x_i:

$$[\mathrm{A}]_C = \sum_{i=1}^{N} x_i [\mathrm{A}]_i \tag{27}$$

Step 4. If $[\mathrm{A}]_C$ satisfies (25) and (26), then go to the next step. Otherwise, adjust them using the rules such as $R_5 \sim R_8$.

R_5: If $[\mathrm{Pb}]_C > [\mathrm{Pb}]^g_{C\max}$ and $[\mathrm{Pb}]_i > [\mathrm{Pb}]^g_{C\max}$, then decrease x_i.

R_6: If $[\mathrm{Zn}]_C > [\mathrm{Zn}]^g_{C\max}$ and $[\mathrm{Zn}]_i > [\mathrm{Zn}]^g_{C\max}$, then decrease x_i.

R_7: If $[\mathrm{S}]_C > [\mathrm{S}]^g_{C\max}$ and $[\mathrm{S}]_i < [\mathrm{S}]^g_{C\min}$, then increase x_i.

R_8: If $[\mathrm{Fe}]_C < 3.5[\mathrm{SiO_2}]_C$ and $[\mathrm{Fe}]_C < 2.0[\mathrm{SiO_2}]_C$, then decrease x_i.

We take the condition in rule R_5 as an example. When $[\mathrm{Pb}]_C > [\mathrm{Pb}]^g_{C\max}$ and $[\mathrm{Pb}]_i > [\mathrm{Pb}]^g_{C\max}$, x_i is adjusted by

$$x_i = x_i + \delta([\mathrm{Pb}]^g_{C\max} - [\mathrm{Pb}]_C)\frac{\partial f(x)}{\partial x_i}, \tag{28}$$

where δ is an experience coefficient which determines the iterative velocity. Then return to Step 3.

Step 5. If the acquired x_i is in the experience range, then take x_i as the optimal ratio of the primary proportioning. Otherwise, choose another experience value as the original value of x_i from the knowledge base, then return to the Step 3.

5. INDUSTRIAL APPLICATIONS

PNN and IGST prediction models were established using the actual production data of the LZSP in a sintering plant. The prediction of the Pb and Zn components in the agglomerate was carried out. The weights w_i $(i = 1, 2)$ for integration of prediction models of the Pb component were chosen to be $w_1 = 0.5006$ and $w_2 = 0.4994$ according to the steps given in Section 3. The integrated prediction model of the Pb component was

$$\hat{y}_t = 0.5006\hat{y}_{1t} + 0.4994\hat{y}_{2t}.$$

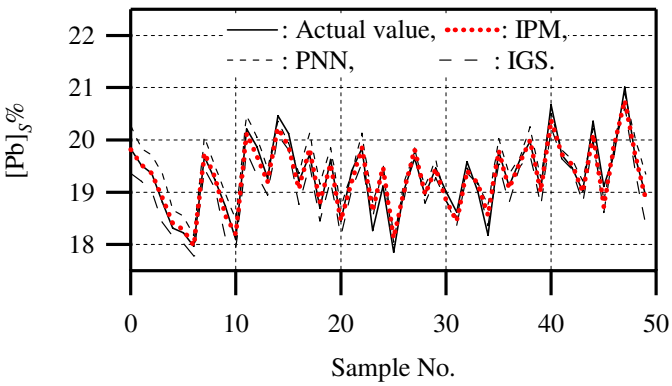

Fig. 2. Prediction Results of Pb component in the agglomerate.

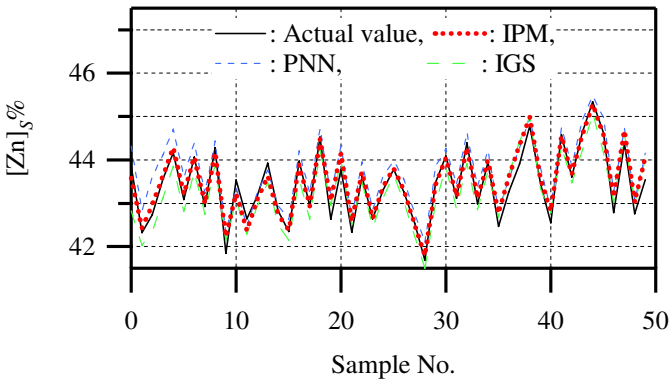

Fig. 3. Prediction Results of Zn component in the agglomerate.

Similarly, the integrated prediction model of the Zn component was

$$\hat{y}_t = 0.5042\hat{y}_{1t} + 0.4958\hat{y}_{2t}.$$

The prediction results of the Pb and Zn components in the agglomerate are shown in Figs. 2 and 3.

The component ratios in the blended material are calculated based on experts' experience in a smelting plant. In order to perform the optimization of the component ratios, to decrease the production cost and to improve the Q&Q, the above method was applied in the sintering blending process of this plant. The application results are shown as follows.

A group of data of the raw material condition are listed in Table 1, and the optimization results for blending (Table 2) are yielded according to the raw material condition in Table 1. The component indexes of the blended material are shown in Table 3 at the blending process and the component of the returned powder have been determined.

The percentage of acceptance for the component ratios in the blended material by using our method is much higher than experts. The cost of our method is also lower than that of experts' operation. In particular, 66.74 CNY are saved per ton in the cost. Since the plant produces 750 ton agglomerate a day, the economical effect is large.

Table 1. Component ratios in the blended material (%) and price (CNY/t).

Material	Pb	Zn	S	CaO	SiO_2	Fe	Price
K_1	15.25	28.69	27.68	4.52	3.27	11.63	3120
K_2	15.03	35.86	28.80	3.64	3.89	11.45	3640
K_3	1.42	46.40	32.04	3.75	2.95	11.34	5300
K_4	18.98	33.46	27.78	0.53	4.83	11.53	3500
K_5	1.18	46.82	32.95	4.22	1.12	10.62	5120
K_6	58.69	3.36	22.95	2.63	1.37	8.37	2120
K_7	2.22	50.78	30.89	2.66	1.09	10.05	4880
K_8	55.66	5.79	19.62	1.66	1.47	8.11	1700
K_9	21.48	28.15	28.36	3.98	1.66	5.82	3700
K_{10}	68.12	5.99	16.89	0.83	0.96	2.98	2510

Table 2. Comparison of the blending ratios between the experts and optimization.

	K_2	K_3	K_5	K_6	K_7	K_9	Cost
Experts' ratio	0.30	0.12	0.08	-	0.14	0.36	4178
Optimal ratio	0.30	-	-	0.02	0.38	0.30	4111

Table 3. Comparison between the required ratio indexed and optimized ratios.

Ratio index	$[Pb]_C$	$[Zn]_C$	$[S]_C$	$[CaO]_C$	$[SiO_2]_C$	$[Fe]_C$
Upper bound	16	39.5	31	5.5	3.5	10
Lower bound	13	35	29	3	2	7
Experts' ratio	13	38	30	1.1	3.2	9.4
Optimal ratio	13	38	29	3.3	2.1	9.2

6. CONCLUSION

In this paper, a Q&Q synthetic methodology for the optimization in the LZSP has been presented. The main points of this study are as follows.

- Based on the PNN and IGST prediction models, an intelligent integrated prediction model has been established based on the concept of information entropy. The model has been used to effectively predict the agglomerate component.
- On the basis of the establishment of the blending optimization model, a Q&Q synthetic methodology has been presented, which integrate the prediction model of the agglomerate component, blending optimization model and the expert reasoning strategy.
- The exact component ratios in the blended material have been obtained and the problem of high cost and low accuracy existed in conventional methods for the lead-zinc sintering blending was solved successfully by this methodology. The application results show that the blending optimization methodology is effective.

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