Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Hierachical intelligent optimization blending system based on production indices for lead-zinc sintering process

Wang Ya-lin*, Yang Chun-hua **, Gui Wei-hua *, Ling Xiang******

School of Information Science and Engineering, Central South University, Hunan Changsha 410083, China
(Tel: +86-731-8876864; e-mail: * ylwang@mail.csu.edu.cn, ** ychh@mail.csu.edu.cn,
*** gwh@mail.csu.edu.cn, **** lingxiang33@163.com)

Abstract: In lead-zinc sintering process, various kinds of lead-zinc concentrates and returning powder from ineligible sintering production are blended and then sintered in updraft sintering machine to produce agglomerate for imperial smelting process. It is required to determine a proper mixture ratio for these materials blended to assure sintering production indices such as agglomerate composition and sintering permeability. Considering the relations between the mixture ratio and the production indices, an intelligent integrated model is firstly constructed to predict agglomerate compositions, which consists of Expertise-and-Mechanism-based model and Supervised Distributed Neural Networks. Based on the composition prediction model and reasoning rules for mixture ratio modification, a hierachical intelligent optimization strategy with expert reasoning is proposed to determine an optimal mixture ratio, which includes multi-objective optimization for the first blending process and area optimization for the second blending process. Practical running results show that the qualified rates of agglomerate compositions are increased by about 7% and the fluctuation of sintering permeability is reduced by 7.0 % through proper blending process according to the optimal mixture ratio, which effectively stabilizes the imperial smelting process.

1. INTRODUCTION

Imperial Smelting Process (ISP) extracts lead and zinc by one step from mixing lead-zinc concentrate, including sintering and smelting process. During the sintering process, various concentrates from different mines and returning powder from ineligible sintering production are first blended, and then sintered in updraft sintering machine to produce agglomerate for smelting processes. The agglomerate compositions and sintering permeability are the important parameters of the sintering process, whose accuracy and stabilization obviously affect the smelting process. The mixture ratio of various materials is one of effective means to control production indexes, so it is necessary to study how to determine the optimal mixture ratio.

Conventional computation methods of optimal mixture ratio involve constructing mathematical models based on mechanism analysis or linear system identification, and computing the target percentages by linear programming, which are extensively applied to sintering process. In these methods the production indexes of next stage, whose inputs are the outputs of blending process, are seldom used to calculate the optimal mixture ratio. In fact whether reasonable or not the mixture ratio is has influence on production indexes and their relationships are very complex in practical process. So expert system (ES) and neural networks (NN) are introduced into optimization of blending process and applied to the coal blending process in an iron and steel plant (Wu et al., 1999; Yang et al., 2000). However they can't be directly used for lead-zinc sintering blending process due to two considerations. Firstly, lead-zinc sintering process is a complex physical and chemical process where solid, liquid and gas states co-exist. It is difficult to accurately predict agglomerate compositions with single mechanism analysis model or NN. Secondly, there are two sub-processes in sintering blending process. The mixture ratio in the second sub-process not only affects agglomerate compositions, but also concerns tsintering permeability associated with some manipulative variables, such as bed temperature and vehicle velocity. So it is necessary to determine an optimal area, not an optimal point. For the modelling of complex industrial process, the combination modelling is verified to be superior to single modelling (Cho et al., 1997) and has been successfully applied to predicting state parameters in sintering process (Wang et al, 2002; Chen and Gui, 2003). So an integrated model of agglomerate composition prediction is constructed, which consists of Expertise-and-Mechanism-based (EM) model and Supervised Distributed Neural Networks (SDNN), taking advantages of mechanism modelling, neural networks, fuzzy classification and expert reasoning method. Based on the composition prediction models and reasoning rules for mixture ratio modification, a hierachical intelligent optimization strategy is proposed to solve blending optimization problem. Aiming at the characteristics of sintering blending process, the optimization problem is decomposed into the first and the second blending optimization stages by an expert reasoning method, where a multi-objective optimization problem in the first stage takes

978-1-1234-7890-2/08/$20.00 © 2008 IFAC

10.3182/20080706-5-KR-1001.1864

cost and stock as optimization objects and mixing concentrate composition indexes as constraints, while an area optimization in the second takes mixture compositions and agglomerate compositions as objects. Consequently, the optimized mixture ratios of the first and second stage meeting requirements of sintering process are obtained by intelligent coordination and reasoning, which has been applied to a non-ferrous smelter. The running results show that Pb, Zn and S composition of agglomerate are improved by 7.1%, 6.5% and 6.9%, respectively and the fluctuation of sintering permeability is reduced by 7%, which effectively stabilizes the imperial smelting process.

The rest of the paper is organized as follows: Section 2 describes production process. Section 3 constructs two composition prediction models for blending process and an integrated model for agglomerate composition prediction. Section 4 proposes an intelligent optimization strategy based on composition prediction and reasoning rule for mixture ratio modification to compute the optimal mixture ratio in two blending sub-processes. Section 5 describes an industrial application and the corresponding results are given. Section 6 summarizes the paper and some conclusions.

2. PROCESS DESCRIPTION

The lead-zinc sintering process is shown in Fig.1.

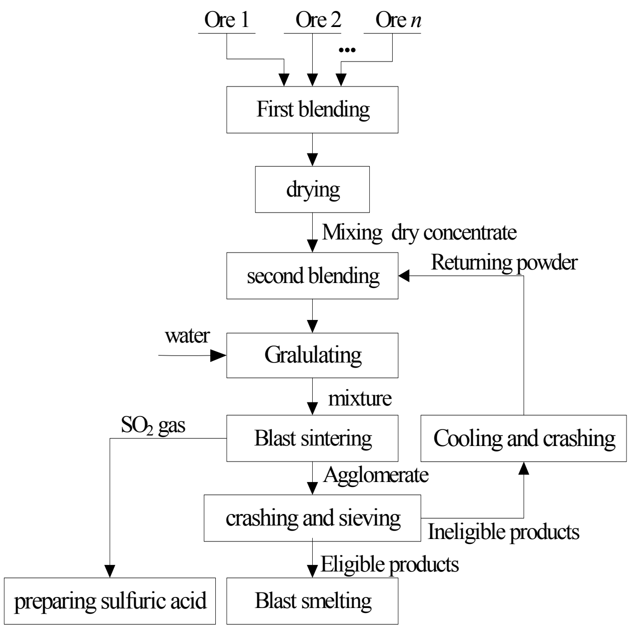


Fig. 1. The lead-zinc sintering process

Different kinds of lead-zinc ores are first blended and dried to become mixing dry concentrate. Then the mixing concentrate and returning powder are blended and granulated. The mixture is oxidized and desulfurated in updraft sintering machine to produce agglomerates and SO_2 is sent to prepare sulfuric acid. After crashed and sieved, eligible agglomerates are put in smelting furnace, while ineligible agglomerates after cooled and sieved are returned in the form of returning powder. In sum, the lead-zinc sintering process includes blending and sintering. The former prepares materials for the latter, and the latter provides materials for smelting process.

In sintering process, agglomerate compositions have to meet requirements of smelting process in a good working order. Under certain sintering conditions (temperature, time, etc.), agglomerate compositions are mainly determined by compositions of the mixture fed in sintering machine, which means the compositions and mixture ratio of returning powder and different ores are the most important factors influencing the agglomerate compositions. Compositions of each kind of ores can be first ascertained, so the key is to determine individual percentage of each kind of ores and returning powder. The ratio of returning powder not only affects the agglomerate compositions, but also is one of key manipulative variables for controlling sintering permeability. So for returning powder ratio, only optimal area need to be determined in the blending process and its optimal value will be given by optimal control of sintering process.

3. COMPOSITION PREDICTION MODEL

Composition prediction models are constructed to describe the composition relationships among different kinds of materials, sintered mixture and agglomerate. Based on the models, the mixture ratio in the blending process can be computed from the required composition of agglomerate and the composition of each material to be blended.

In lead-zinc sintering blending process, the composition prediction models consist of the first blending relation model, the second blending relation model and agglomerate composition prediction model, which are used to predict Pb, Zn and S compositions. The predictions of Fe, CaO and SiO_2 composition are not discussed in the paper for they generally satisfy industrial requirements.

3.1 Composition Prediction Models in Blending Process

There are only physical changes during the blending process from individual material to sintering mixture, the first blending relation model and the second blending relation model are linearly described with (1) and (2), respectively.

$$w(E)_c = \frac{1}{1-h_1} \times \sum_{i-1}^{N} m_i \times w(E)_i \, , \sum_{i=1}^{N} m_i = 1 \tag{1}$$

$$w(E)_M = \frac{1}{1+h_2} \times \left[b \times w(E)_C + (1-b) \times w(E)_R \right] \tag{2}$$

Where $w(E)$ denotes prediction composition; N the number of Lead-zinc ores; m_i the mixture ratio of the i-th kind of ore; h_1 and h_2 the removing and adding water ratios, respectively; b the mixture ratio of mixing concentrate in the second blending, whose value belongs to [0,1]; subscript i the i-th kind of ore, C the mixing concentrate, M the sintering mixture, and R the returning powder.

3.2 Composition Prediction Model of Agglomerate

The main chemical reactions in the sintering process include desulfuration of zinc and lead concentrates, and oxidization of iron. By the material equilibrium of these reactions, the composition models of lead and zinc can be described in (3).

$$w(Pb)_S = \frac{w(Pb)_M - w(Pb)_L}{1-R_L} - (1-R_S)\Delta w(Pb) \quad (3a)$$

$$w(Zn)_S = \frac{w(Zn)_M - w(Zn)_L}{1-R_L} - (1-R_S)\Delta w(Zn) \quad (3b)$$

where $w(Pb)$ and $w(Zn)$ are lead and zinc composition, respectively; subscript S agglomerate, M sintering mixture, and L the loss in reaction; $\Delta w(Pb)$ and $\Delta w(Zn)$ induced from data statistic the composition difference between agglomerate and returned powder; R_S caking ratio and R_L the loss ratio. In general, $\Delta w(Pb)$, $\Delta w(Zn)$ and R_L have no change and are taken as constants. $w(Pb)_L$, $w(Zn)_L$ and R_S are set based on statistical data and the following empirical rules.

R^{001}: if $w(Pb)_M$ increases then $w(Pb)_L$ and R_S increases.
R^{002}: if $w(Zn)_M$ increases then $w(Zn)_L$ increases.
R^{003}: if vehicle velocity V increases then $w(Pb)_L$ and R_S decreases. ……

The above EM model reflects process situations to some extent. It is particularly sensitive and robust in abnormal and abrupt-changing cases. But the prediction model is not precise enough due to some hypothesis, statistical and empirical estimate. On the other hand, NN is capable of arbitrary approximating non-linearity (Chen and Billings, 1992) and is used for industrial process modelling (Yang et al., 2003). But it strongly relies on measurement data and lacks of physical foundation. Moreover NN sometimes outputs incompatible results with practical rules. Taking advantages of the two models, an integrated model shown in Fig.2 is proposed to realize reliable and accurate prediction of agglomerate compositions including composition prediction unit, expert coordinating unit and expert learning unit.

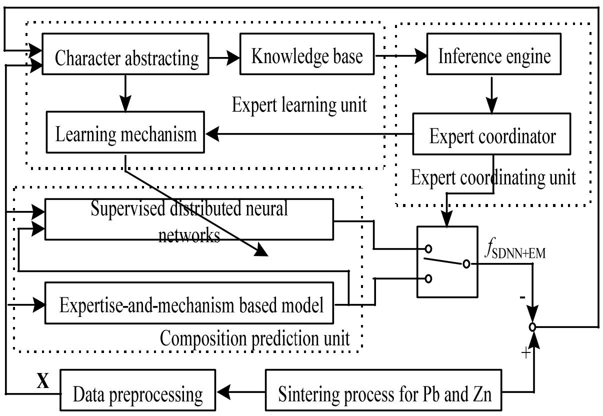


Fig. 2. The integrated model for predicting agglomerate's composition

The composition prediction unit is composed of SDNN and EM model in series and parallel, where the output of EM model is taken as the input of SDNN. Expert coordinating unit aims to coordinate the output of SDNN and EM model, and to decide when and by which learning mechanism SDNN model goes into learning status. Expert learning unit supervises and appraises the work of expert coordinating unit in real-time, and effectively enriches and modifies expert coordinating rule and the two models of composition prediction unit. SDNN consists of four inputs, one output and a distributed model, Where four inputs are V, $w(Pb)_M$, $w(Zn)_M$ and $w(S)_M$., output is $w(Pb)_S$ or $w(Zn)_S$, and the distributed model includes series of sub-NNs, built based on different subset decided by supervised clustering method. The output of SDNN is sum of the outputs of sub-NNs with different weights obtained by fuzzy classifier.

For simplification, $f_{SDNN+EM}(X)$ is used to represent the integrated model. The integrated model of $w(Pb)_S$ is

$$w(Pb)_S = f_{SDNN+EM}\left(w(Pb)_M, w(Zn)_M, w(S)_M, V, T\right) \quad (4)$$

Where V is vehicle velocity of sintering machine, T is bed temperature. The prediction of $w(Zn)_S$ is similar to (4). Under the circumstance of a certain V and T, Pb and Zn composition of agglomerate are closely related to Pb, Zn and S composition of sintering mixture.

4. HIERACHICAL INTELLIGENT OPTIMIZATION FOR BLENDING PROCESS

4.1 Optimization Strategy

Optimization computation of the blending process aims at determining the optimal mixture ratio to produce suitable agglomerate, reduce material cost and stock and improve the benefits. Firstly the first and the second blending processes are relatively independent. Secondly the mixture ratio of the second blending only needs to acquire a reasonable zone in the blending process. Finally cost and stock take the returning powders into no account. So in lead-zinc sintering process, its blending optimization (see Fig.3) includes multi-objective optimization of the first blending and area optimization of the second blending.

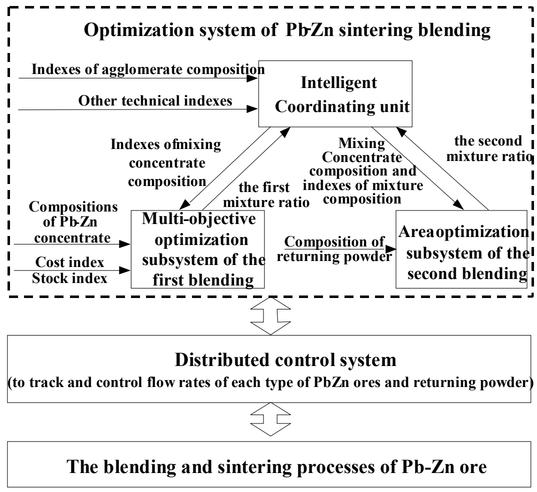


Fig. 3. Optimization strategy for the blending process

The optimization for the first blending takes cost and stock as optimization objects and subjects to mixing concentrate composition indexes as constraints. Given the definite compositions of mixed concentrate and returning powders, the optimization for the second blending takes the mixture compositions as objects. Intelligent coordination unit gets information from the first and the second subsystems and respectively provides composition indexes of the mixing concentrate and the mixture for the two subsystems. By intelligent coordination, the optimized mixture ratios make agglomerate compositions and other sintering technical indexes meet requirements.

The optimization system uses a reasoning strategy based on composition prediction models and rule models, and combines forward chaining and model-based reasoning to compute the target mixture ratio from the productive indexes and the compositions of each material. Finally using the computed values and the total flow rate of the blending process, the system calculates the target flow rate of each material and sends it to Distributed Control System (DCS) to ensure that the actual flow rates track the target flow rates.

4.2 Rule Models

Based on a great deal of statistical data and empirical knowledge of experts and veteran operators, production rule model is used to describe intelligent coordinating and expert reasoning process in the optimization system.

According to the proposed optimization strategy, there are four kinds of rule models. The first one RM1 is used as inducing the composition indexes of sintering mixture, for example, the rule R^{101}-R^{102}.

R^{101} : if $w(Pb)_S > w(Pb)_S{}^g{}_{\max}$ and $w(S)_M$ is larger then decrease $w(Pb)_M$.
R^{102} : if $w(Zn)_S > w(Zn)_S{}^g{}_{\max}$ and $w(S)_M$ is smaller then decrease $w(Zn)_M$ and increase $w(S)_M$. ……
The second RM2 determines the mixture ratio of the first blending, for example, the rule R^{201}-R^{202}.

R^{201} : if $w(Zn)_C < w(Zn)_C{}^g{}_{\min}$ and $w(Zn)_i > w(Zn)_C{}^g{}_{\max}$ then increase m_i.
R^{202}: if $w(S)_C > w(S)_C{}^g{}_{\max}$ and $w(S)_i < w(S)_C{}^g{}_{\min}$ then increase m_i. ……
The third RM3 determines the optimization zone of the second blending, for example the rule R^{301}-R^{302}.

R^{301}: if $b_{Pb\text{-}opt} \cap b_{Zn\text{-}opt} \cap b_{S\text{-}opt} \cap b_{exp} = 0$ then $b_{opt} = b_{\exp}$.
R^{302}: if $b_{opt} \cap b_{S\text{-}opt} \neq 0$ then $b_{opt} = b_{opt} \cap b_{S\text{-}opt}$.……
And the fourth RM4 is used as coordinating the composition indexes of mixed concentrate, for example, the rule R^{401}-R^{402}.

R^{401}: if $w(Pb)_M{}^c{}_{\min} > w(Pb)_M{}^g{}_{\max}$ and $w(Pb)_C{}^g{}_{\max} - w(Pb)_C{}^g{}_{\min} > \alpha_1$ then decrease $w(Pb)_C{}^g{}_{\min}$.
R^{402}: if $w(S)_M{}^c{}_{\max} < w(S)_M{}^g{}_{\min}$ and $w(S)_C{}^g{}_{\max} - w(S)_C{}^g{}_{\min} > \alpha_2$ then increase $w(S)_C{}^g{}_{\max}$.……
Here, $w(Pb)_S{}^g{}_{\max}$ and $w(Pb)_S{}^g{}_{\min}$ denote maximum and minimum index of agglomerate Pb composition, respectively; $w(Pb)_C{}^g{}_{\max}$ and $w(Pb)_M{}^g{}_{\max}$ are the maximum Pb composition index of the mixed concentrate and the mixture, respectively; $w(Pb)_M{}^c{}_{\max}$ is the maximum Pb composition index of the mixture determined by optimization computation; $b_{Pb\text{-}opt}$ denotes the optimal area of the second blending process meeting requirement of the mixture Pb composition; $b_{\exp}$ is the empirical area determined by sintering permeability; b_{opt} is the optimal area determined by subsystem. α_1 and α_2 are the range threshold of mixing concentrate Pb and S composition, respectively.

4.3 Multi-objective Optimization for the First Blending

The optimization model of the first blending process is

$$\min J_1 = \sum_{i=1}^{N} C_i \times m_i \tag{5}$$

$$\min J_2 = \sum_{i=1}^{N} S_i \times m_i$$

$$s.t.\begin{cases} w(Pb)^g_{C\min} \le w(Pb)_C = \dfrac{1}{1-h_1}\sum_{i=1}^{N} m_i \times w(Pb)_i \le w(Pb)^g_{C\max} \\ w(Zn)^g_{C\min} \le w(Zn)_C = \dfrac{1}{1-h_1}\sum_{i=1}^{N} m_i \times w(Zn)_i \le w(Zn)^g_{C\max} \\ w(S)^g_{C\min} \le w(S)_C = \dfrac{1}{1-h_1}\sum_{i=1}^{N} m_i \times w(S)_i \le w(S)^g_{C\max} \end{cases}$$

Where C_i is the cost of the i-th kind of ore, S_i is its stock.

By introducing stock influence factor into the cost, the multi-objective of (5) is transformed into the single objective of (6)

$$\min J = \sum_{i=1}^{N} C_i K_i m_i \tag{6}$$

where K_i is stock influence factor, consisting of three elements $\{1-\beta,\ \beta,\ 1+\beta\}$.If S_i is higher, then K_i is $1-\beta$; if S_i is normal, K_i is β; and if S_i is smaller, K_i is $1+\beta$.

For the above optimization model, the mixture ratio of the first blending is determined through the following steps.

Step 1, Select suitable empirical values from the knowledge base as the initial values of m_i (i=1,2,…,N).

Step 2, Known m_i, compute $w(E)_C$ according to (1).

Step 3, If $w(E)_C$ meets the composition indexes $w(E)_C{}^g{}_{\max}$ and $w(E)_C{}^g{}_{\min}$ provided by IC unit, then take next step, otherwise adjust m_i by the rule models RM2. For example, when $w(Pb)_C > w(Pb)_C{}^g{}_{\max}$, and $w(Pb)_i > w(Pb)_C{}^g{}_{\max}$, then let

$$m_i = m_i + \gamma\left(w(Pb)^g_{C\max} - w(Pb)_C\right)\frac{\partial J}{\partial m_i} \tag{7}$$

and return to step 2. Where γ is an empirical value determining the convergence rate of iterative computation.

Step 4, Check whether m_i is in the empirical range. If so, stop the computation and output the optimal m_i. If not, reset the initial m_i and return to step 2. If suitable m_i can't be obtained in the given iteration times, stop the computation and report that useful m_i doesn't exist and output the empirical m_i determined by the man-machine interface.

4.4 Area Optimization for the Second Blending

Different from the first blending, the optimization process of the second blending takes the mixture compositions as the objects to determine its satisfactory zone.

Known $w(Pb)_R$ and $w(Pb)_C$, take $w(Pb)_M{}^g{}_{\max}$ and $w(Pb)_M{}^g{}_{\min}$ to (2), and then obtain the mixture ratio zone of the second blending, $b_{Pb\text{-}opt}=[b_{Pb\text{-}\min},\ b_{Pb\text{-}\max}]$, meeting the requirements of the mixture Pb composition index.

$$b_{Pb-\min} = \frac{w(Pb)_R - (1+h_2)\,w(Pb)^g_{M\max}}{w(Pb)_R - w(Pb)_C} \qquad (8)$$
$$b_{Pb-\max} = \frac{w(Pb)_R - (1+h_2)\,w(Pb)^g_{M\min}}{w(Pb)_R - w(Pb)_C}$$

The $b_{Zn\text{-}opt}$ and $b_{S\text{-}opt}$ are obtained by the same method. The optimization zone b_{opt} is the intersection of all zones, namely

$$b_{opt} = b_{\exp} \cap b_{Pb-opt} \cap b_{Zn-opt} \cap b_{S-opt} \qquad (9)$$

If (9) is void, b_{opt} will be determined to the rule model RM3.

4.5 Intelligent Coordinating Unit of Optimization System

The IC unit of optimization system works as following steps.

Step 1, According to the agglomerate composition indexes, determine $w(E)_M{}^g{}_{\max}$ and $w(E)_M{}^g{}_{\min}$ by expert reasoning based on the prediction model (4) and rule model RM1, where E represents Pb or Zn, $w(S)_M{}^g{}_{\max}$ and $w(S)_M{}^g{}_{\min}$ are given by production.

Step 2, Set the initial optimal interval $[b_{\min},b_{\max}]$ of the second blending process, determine $w(E)_C{}^g{}_{\max}$ and $w(E)_C{}^g{}_{\min}$ according to the mixture composition indexes and the mixture composition prediction models (2). For example, the Pb composition index in mixed concentrate has

$$w(Pb)^g_{C\max} = \frac{(1+h_2)\,w(Pb)^g_{M\max} - (1-b_{\min})\,w(Pb)_R}{b_{\min}} \qquad (10)$$
$$w(Pb)^g_{C\min} = \frac{(1+h_2)\,w(Pb)^g_{M\min} - (1-b_{\max})\,w(Pb)_R}{b_{\max}}$$

Step 3, Provide the mixed concentrate composition indexes and the mixture composition indexes for the optimization subsystems of the first blending and the second blending.

Step 4, According to (1) and m_i obtained by the first blending optimization subsystem, compute the mixing concentrate composition for the second blending subsystem.

Step 5, According to (2) and b_{opt}, compute the range of the mixture composition $[w(E)_M{}^c{}_{\min},\ w(E)_M{}^c{}_{\max}]$. If the mixture composition does not satisfy the indexes, modify the mixing concentrate composition indexes by the rule RM4, and then return to step 3. Otherwise determine whether m_i and b_{opt} are reasonable. If so, sent them to DCS and control them. If not, alarm and determine them by empirical value.

5. INDUSTRIAL APPLICATIONS

The blending optimization system developed according to the above optimization strategy has been applied to the lead-zinc blending process of a nonferrous metal smeltery since 2005.

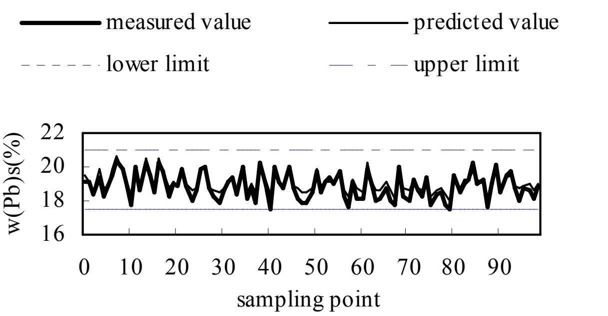
The integrated models predicting agglomerate compositions are constructed based on the data culled from production data in 2003 and 2004. By training SDNN consists of three sub-BP networks and each BP networks has an input layer with 4 neurons, a hidden layer with 15 neurons and an output layer with one neuron. The integrated models are modified continuously by the learning mechanism based on the renewal of production data to adapt to changes in the environment and operating conditions

The optimization strategy based on composition prediction model and rule model are implemented on an industrial computer with a special program package written in Visual C++. The optimization system obtains the data of material composition (refreshed per 2 hours) from the server in the information management centre through industrial Ethernet, and computes the optimization mixture ratio and the corresponding target flow rates of each individual material to be blended based on sintering production indexes. Then each target flow rate is transmitted to Yokongawa μ XL Distributed Control System (YDCS), and the tracking control of the target flow rates is implemented by YDCS.

The practical running results from 2005-9-19 0:00 to 2005-9-27 6:00 are shown in Fig 4. The agglomerate compositions can be obtained per 2 hours. So there are 100 groups of agglomerate compositions in Fig. 4. Where, the composition indexes of agglomerate and the production empirical values are in (11), which are used to computing the mixture ratio.

$$17.5\% \le w(Pb)_S \le 21\%, 41\% \le w(Zn)_S \le 45\%, w(S)_S \le 1\% \qquad (11a)$$
$$5\% \le w(S)_M \le 7\% \qquad (11b)$$

The mean measurement values of $w(Pb)_S$, $w(Zn)_S$ and $w(S)_S$ are 19.02%, 42.25% and 0.695%, and the mean prediction values of $w(Pb)_S$ and $w(Zn)_S$ are 19.27% and 42.84%, respectively. The results show that the measurement values of agglomerate satisfied the requirements of (11a).



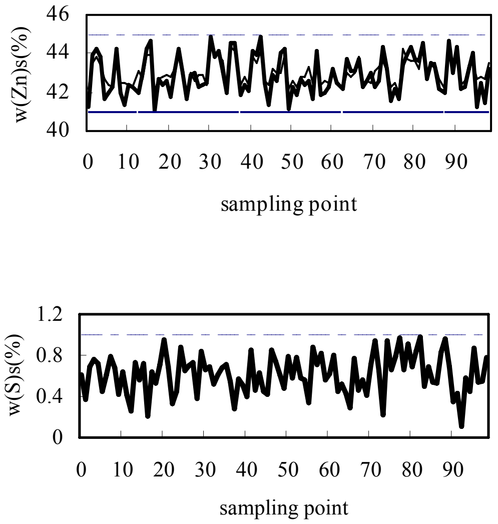


Fig. 4. Measurement and prediction values of agglomerate composition

The statistical data of related performance index for more than a year are list in Table 1 since the optimization system was put into service. Clearly, the production indexes have been greatly improved from Table 1.Where Q_P, Q_Z and Q_S is the qualified rate of Pb, Zn and S, respectively. ΔP denotes fluctuation of synthetic permeability in the sintering process.

Table 1. The statistics data comparisons of performance index

	Q_P	Q_Z	Q_S	ΔP
Former	90.3%	88.2%	91.6%	10.3%
Current	97.4%	94.7%	98.5%	3.3%
Improved	+7.1%	+6.5%	+6.9%	-7%

6. CONCLUSIONS

In this paper an integrated model is constructed to predict compositions of agglomerate in lead-zinc sintering process based on mechanism analysis, measured data and empirical knowledge, which consists of EM model and SDNN model. A hierachical intelligent optimization strategy with expert reasoning is proposed to compute the optimal mixture ratio of sintering blending process so as to assure that the agglomerate compositions satisfy the production indexes. The blending optimization is implemented through multi-objective optimization for the first blending, area optimization for the second blending, and intelligent coordination between them. The corresponding iterative algorithms are presented, which use forward chaining and model-based reasoning based on composition prediction model and rule model. The optimal blending system using the proposed optimization strategy has been applied to industrial production since 2005, the qualified rates of agglomerate Pb, Zn and S composition are improved by 7.1%、6.5% and 6.9%, respectively and the fluctuation of sintering permeability is reduced by 7%, which stabilizes the agglomerate compositions and the permeability. The practical application shows its effectiveness.

ACKNOWLEDGE

This work was supported in part by the National Natural Science Foundation of China (NO: 60634020 & 60574030), National Fundamental Research and Development Program of China (2002CB312200), the Natural Science Foundation of Hunan Province, China (06FD026).

REFERENCES

Wu M, Nakano Michio and She J H (1999). A Model-based Expert control Strategy using Neural Network for the Coal Blending Process in an Iron and Steel Plant. *Expert systems with Application*, **16(3)**, 271-281.

Yang C H, Shen D Y, Wu M and et al (2000). Synthesis of qualitative and quantitative methods in a coal blending expert system for coke oven. *Acta Automatica Sinica,* **26(2)**,226-232. (in Chinese)

Cho S, Cho Y, Yoon S (1997). Reliable rool force prediction in cold mill using multiple neural networks. *IEEE Tran. on Neural Networks.* **8(4)**, 874-882.

Wang Y W, Gui W H and Wang Y L (2002). Integrated model for predicting burning through point of sintering process based on optimal combination algorithm. *The Chinese Journal of Nonferrous Metals*, **12(1)**, 191-195. (in Chinese)

Chen X F and Gui W H (2003). An integrated modeling method for prediction of sulfur content in agglomerate. *Journal of Central South University of Technology..* **10(2)**, 145-150.

Chen S and Billings S A (1992). Neural networks for nonlinear dynamic system modeling and identification. *Int. J. Control*, **56(2)**, 319-346.

Yang C H, Deconinck Geert and Gui W H (2003). An Optimal Power-Dispatching Control System for the Electrochemical Process of Zinc Based on Backpropagation and Hopfield Neural Networks. *IEEE Trans. on Industrial Electronics*, **50(5)**, 953-961.