15th Triennial World Congress, Barcelona, Spain

A PREDICTION MODEL OF SULFUR *
BASED ON INTELLIGENT INTEGRATED STRATEGY

Xiaofang Chen Weihua Gui Yalin Wang Min Wu Chunhua Yang

Department of Automatic Control Engineering, Central South University
Changsha, Hunan, 410083, P.R.China

Abstract: Considering the prediction of sulfur in agglomerate in sintering process, a prediction model based on intelligent integrated strategy is put forward in this paper, where the mathematical model calculates the sulfur content in agglomerate following material balance equation with some parameters predicted by NN method, while the expert rule model describes the relationship between sulfur quantity and key factors. An intelligent coordinator based on fuzzy logic is proposed to synthesize the output of the models. The industrial application proved its effectiveness in sintering production. *Copyright ©2002 IFAC*

Keywords: prediction; neural network; fuzzy inference; process models; expert systems

1. INTRODUCTION

Sintering is a desulfuration burning and melting process of Pb-Zn mine to provide agglomerate for Pb-Zn production in Imperial Smelting Process (ISP). If the sulfur content in agglomerate exceeds 1%, the smelting process can' t run fluently and the conditions are deteriorated remarkably. So important a parameter as it is in sintering process, predicting the sulfur content in agglomerate is imperative for optimization of operative conditions and controlling parameters.

Pb-Zn sintering process is a very complex physicochemical process with nonlinearity, time variety, strong coupling and uncertainty. The relationships are too complicated to describe either in conventional ways or by simple intelligent modeling methods. Conventional mathematical model is found fruitless because some parameter in the equation based on material balance is unsolvable. The parameter can be obtained by chemical test, but the test data is lagged and inapplicable for prediction. Some simple NN model is also experimented and found futile as a result of complexity of the process and low accuracy of data. The simple NN model based on measured data does not take chemical mechanism into consideration and conventional model refuses the information included in measured data. Both of them omit some helpful information. So a new reasonable modeling technique to synthesize the information is badly needed to overcome the difficulty.

Intelligent technologies and theories, such as expert system (Åström K.J., et al., 1986), neural network (Chen S., et al., 1992), fuzzy logic (Chiu S., 1994; French S., 1995) and so on, have many advantages in dealing with multi-variab1e, non1inear, half quantitative and qualitative data. Expert systems, which are based on empirical knowledge, have been used for process control (Wu M., et al., 1999). Neural networks are powerful tools for modeling and control of complex systems (Nikravesh M., 1996). These intelligent techniques combined with traditional methods have been applied to modeling for comp1ex industria1 processes (Wu M., et al., 2000; Wang Y.L., et al., 2000).

In this paper, a prediction model based on intelligent integrated strategy is described in which different intelligent mode1ing methods are employed in different conditions. The sulfur content in agglomerate is calculated following a materia1 balance equation. Due to that some unknown

*Supported by National 863 High Tech. Program of China (Grant Number: 2001AA411040)

parameter in the equation is unavailable at real time, an NN model is introduced to evaluate the parameter in advance. An expert rule model based on a great deal of production data and empirical knowledge is proposed to estimate the value. Finally an intelligent coordinator is introduced to judge process conditions and to determine the ratio of result calculated by each model.

The rest of the paper is organized as follows: The function and structure of different components of intelligent integrated model is presented in section 2, where the connection among them is described to show how they work together and keep up with sintering process. The mathematical model based on material balance combined with neural network prediction is presented in section 3. The rule model based on empirical knowledge is presented in section 4. The intelligent coordinator based on fuzzy choosing strategy is described in section 5. These three sections are essential parts of intelligent integrated model. In the following section the running results of industrial application are provided to prove its effectiveness. At last, the features and advantages of the prediction model are concluded.

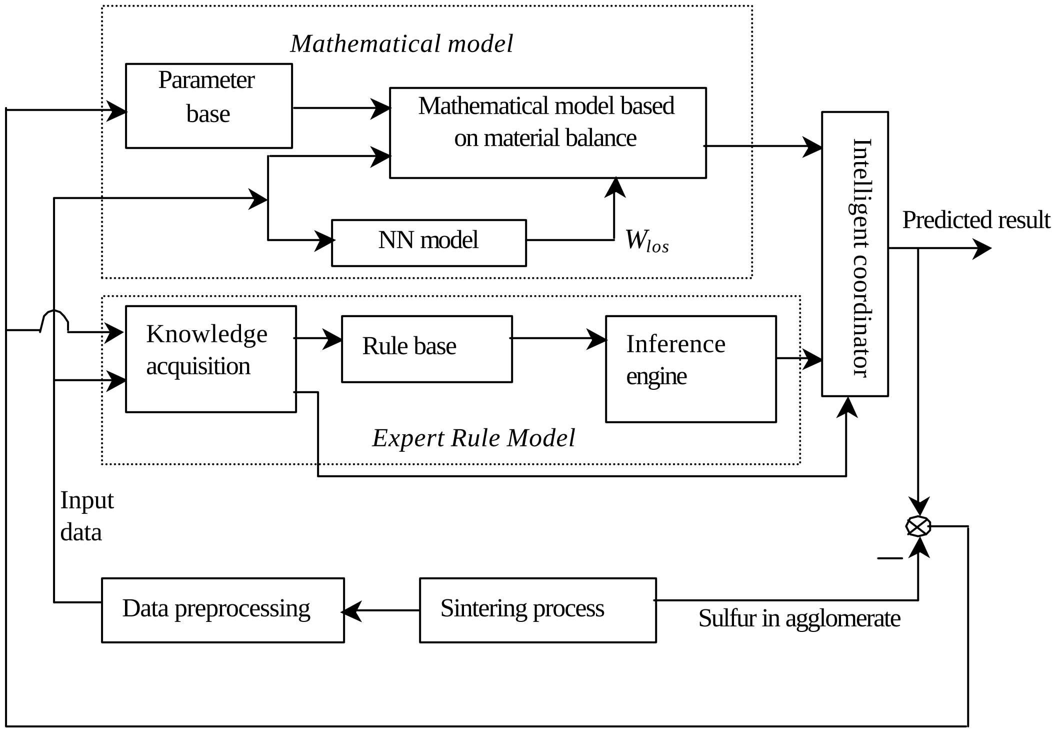

Fig. 1. The framework of intelligent integrated model

2. THE FRAMEWORK OF PREDICTION MODEL BASED ON INTELLIGENT INTEGRATED STRATEGY

According to the sintering process data, different modeling methods have been tried by simulation test, which indicates that none of them is singly successful while each has some advantages and disadvantages in analysis.

An NN model to fit the input and output data is possible to display precise prediction but the problems of slow training, local minimum and overfitting make it unreliable and lead to bad generalization. Mathematical model based on material balance equation reasonably and precisely describes the relationship of input and output sulfur during sintering process. But a parameter in the equation, the sintering loss of sulfur is not available in advance for prediction. Expert rule model provides qualitative estimation of sulfur in agglomerate based on reaction mechanism and process experience. It is apparent that proper integration of these methods will compensate the drawbacks of each and improve the prediction accuracy of sulfur in agglomerate.

The framework of intelligent integrated model to predict the sulfur content in agglomerate is showed in Fig.1. The integrated model consists of mathematical model and expert rule model parallel connected by the intelligent coordinator for estimating the condition from data and deciding how the models are integrated. The coordinator is regulated with characters obtained from practical data.

Mathematical model based on material balance equation is composed of parameter base, mathematical equation and neural network prediction model. The mathematical equation is derived from chemical analysis of sulfur balance in sintering reactions. In the equation, some parameter is obtained by NN prediction model. The parameters are tuned according to process data and predictive errors to guarantee the reliability of the equation. Expert model based on rules acquired from process data, reaction mechanism and process experience is composed of knowledge acquisition, rule base and inference engine. The knowledge acquisition refines rules from data and keeps them in the rule base as well as estimates present conditions for intelligent coordinator. The inference engine utilizes these rules and offers analytic prediction of expert rule model. The intelligent coordinator combines the results of mathematical model and expert rule model via fuzzy operation according to conditions of input data. When the condition is good and most parameters are fluctuant within a limited range, the result of mathematical model weighs more in final prediction. When the disturbance is serious and conditions seem abnormal, the result of expert rule model takes more effect to give estimation according to various process conditions.

When the integrated model running on-line, the prediction data is compared with industrial data, the error of which is used for adjusting rules' bounds and parameters in mathematical model, and a data preprocessing block is applied to eliminate unwanted or false data.

3. MATHEMATICAL MODEL COMBINED WITH NEURAL NETWORK

In sintering process, after the mixture of Pb-Zn mine and returned powder enters sintering machine, the sulfur is burned to form sulfur dioxide as well as agglomerate and returned powder are produced. The former is put into smelting process and the latter is returned to sintering machine. Because the data of sulfur in agglomerate is not as reliable as sulfur in returned powder as well as the latter is easy to describe in formula, an equation about sulfur in returned powder is set up at first, in a part of which NN model is used. Then the relationship between the sulfur content in agglomerate and in returned powder is found by linear regression.

3.1 Equation of material balance

By analysis of sintering process, all the sulfur added in sintering machine turn into four parts in the end:

(Ⅰ) enters acid producing system in SO_2;

(Ⅱ) gives away into air in form of SO_2 or S;

(Ⅲ) remains in agglomerate and returned powder in the form of sulfate and sulfide;

(Ⅳ) remains in dust and ash.

Item (Ⅰ) is measurable because the flux and density of smoke for acid system is detected. Item (Ⅱ) and (Ⅳ) are immeasurable and related to reaction intensity. In (Ⅲ), sulfur in agglomerate and returned powder is influenced by process conditions and to be studied.

According to the relationship, the material balance equation is set up like this,

$$W_M[S]_M = k_1 D_{SO_2} Q_{gas} + W_S[S]_S + W_R[S]_R + W_{los} \tag{1}$$

Where W_M is the sintering mixture per hour (t/h), $[S]_M$ is the sulfur content in the mixture, k_1 is the conversion coefficient of SO_2 and $k_1 = 32/(22.4\times100) = 0.0143$, D_{SO_2} is the density of SO_2 (%) in sintering smoke, Q_{gas} is the flux of smoke per hour (Knm^3/h), W_S is the mass of agglomerate produced per hour (t/h), $[S]_S$ is the sulfur content in the agglomerate, W_R is the mass of returned powder produced per hour(t/h), $[S]_R$ is the sulfur content in the returned powder, W_{los} is the loss of sulfur in sintering, including loss in the atmosphere, dust and ash.

The average sulfur content in output solid is

$$[S]_{ave} = (W_S[S]_S + W_R[S]_R)/(W_S + W_R) \tag{2}$$

and

$$W_S + W_R = h_l W_M \tag{3}$$

Where h_l is the mass ratio of output solid to input material. Duo to dust loss and sulfur emitted into atmosphere, the input material is diminished during sintering process. Large amount of statistical data has verified roughly that h_l =90% and $[S]_{ave} = a_r[S]_R$ where a_r =0.88。

Let

$$k_2 = h_l a_r \tag{4}$$

Eq. (1) is solved from (2), (3) and (4) and $[S]_R$ is represented as

$$[S]_R = (W_M[S]_M - k_1 D_{SO_2} Q_{gas} - W_{los})/(k_2 W_M) \tag{5}$$

To solve $[S]_R$, all parameters in (5) except W_{los} are determined in advance by detection or evaluation. The method to predict W_{los} is discussed as follows.

3.2 NN model to predict the loss of sulfur

W_{los} is related to the density of SO_2 D_{SO_2}, the total input sulfur $W_M[S]_M$ and bed back temperature T_b and the relationship is nonlinear. Owing to the property of function approximation of neural network, an NN model of multiplayer feedforward network is introduced to describe it as formulated in (6).

$$W_{los} = f_{NN}(D_{SO_2}, W_M[S]_M, T_b) \tag{6}$$

To avoid slow training and trapping into local minimum, the NN model is trained by Levenberg-Marquardt (L-M) algorithm (Hagan M. T., et al., 1994), in which the weight vectors is updated as

$$w_{k+1} = w_k - [J^T J + mI]^{-1} J^T e \tag{7}$$

Where J is a Jacobian matrix containing first derivatives of the network errors with respect to weights and bias which are computed by standard BP algorithm. e is the network error vector and $e=[e_1,e_2,\cdots,e_Q]^T$, m is a parameter adjusted to the performance function.

To training the NN model, 126 groups of process data, which involve $W_M[S]_M$, D_{SO_2} and T_b, are chosen according to corresponding time. Expected value of W_{los} in sample data is able to be calculated by Eq.(1) since the output data is given.

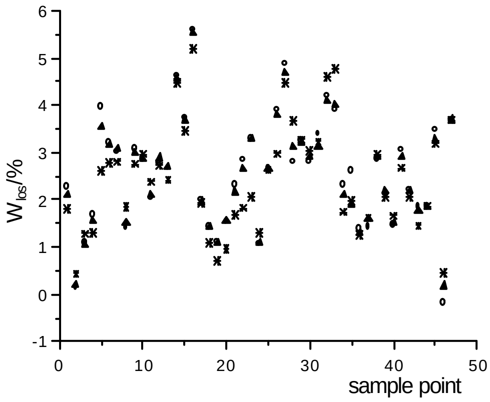

Fig. 2. Predictive curves of the loss of sulfur

D_{SO_2}, $W_M[S]_M$ and T_b are the input variables of NN model, W_{los} is the output. 79 groups of data are used as learning set and afterwards the model is tested for prediction by 47 groups of data. The figure of predictive data and expected data is showed in Fig.3, where the circles denote expected W_{los}, the triangles denote predictive W_{los}. Compared with the result given by linear regression method (as the stars indicate in Fig.2), the neural network model is better in precision.

3.3 Mathematical model combined with NN

An approximate linear relation between the sulfur content in agglomerate and in returned powder is found to be true from process data (Fig.3). The dotted line shows the sulfur content in agglomerate and the solid line shows that in returned powder. According to the formula

$$[S]_S = \boldsymbol{a}[S]_R + \boldsymbol{b} \qquad (8)$$

Least square method is applied to fitting (8). As the result, $a=0.592, b=-0.218$.

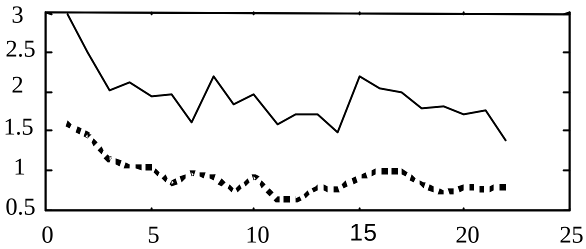

Fig. 3. The sulfur content in agglomerate and in returned powder

While W_{los} is gained by NN model, (5) and (8) are solvable equations which can be formulated in an integrated way as Eq. (9).

$$[S]_S = f_{NN+MA}(W_M, [S]_M, D_{SO_2}, Q_{gas}, T_b) \qquad (9)$$

The analytical formulation of $[S]_S$ is

$$[S]_S = \frac{a\cdot(W_M[S]_M - k_1 D_{SO_2} Q_{gas} - W_{los})}{k_2 W_M} + b \qquad (10)$$

Where W_M, $[S]_M$ and D_{SO_2} are detectable, k_1, k_2, a and b are determined constants which can be adjusted, W_{los} is predicted by the NN model.

4. RULE MODLE BASED ON EMPIRICAL KNOWLEDGE

Rule model based on empirical knowledge from long-term production is complementary for the mathematical model to deal with abnormal process conditions. By analysis, D_{SO_2}, $W_M[S]_M$ and T_b are selected as input variables of rule model for estimation of $[S]_S$. In general, the behavior of expert controller is characterized by a set of linguistic control rules. According to various states of sintering process, different conditions and corresponding estimations are provided in the form of generalized rules by knowledge acquisition module.

The variety ranges of input and output variables are divided into 5 classes as Negative Big, Negative Small, Zero, Positive Small and Positive Big. Table 1.is the subset distribution of Input and output variables. The distribution bounds are decided by present experience and data and are adjustable via knowledge acquisition module.

Table1. Subset distribution of Input and output variables

Subset of range	NB	NS	ZO	PS	PB
T_b	<150℃	150-250℃	250-400℃	400-500℃	>500℃
$W_M[S]_M$	<11	11-12	12-13	13-14	>14
D_{SO_2}	<3%	3-4%	4-5.5%	5.5-6%	>6%
$[S]_S$	<0.6%	0.6-0.8%	0.8-1.0%	1.0-1.5%	>1.5%

The formulation of rule model is

Rule^i: IF $x_1 \in A_{i1}$

ANDIF $x_m \in A_{im}$

THEN $y \in W_i$

The rules based on empirical knowledge are described as Rule$^{1\text{-}29}$.

Rule$^{1\text{-}5}$:

IF $T_b \in$ NB

ANDIF $D_{SO_2} \in$ NB

THEN $[S]_S \in$ PB;

ANDIF $D_{SO_2} \in$ NS

THEN $[S]_S \in$ PB;

ANDIF $D_{SO_2} \in$ ZO

THEN $[S]_S \in$ PB;

ANDIF $D_{SO_2} \in$ PS

THEN $[S]_S \in$ PS;

ANDIF $D_{SO_2} \in$ PB

THEN $[S]_S \in$ PS;

...

Rule$^{27\text{-}29}$:

IF $W_M [S]_M \in$ PB

ANDIF $D_{SO_2} \in$ NS

THEN $[S]_S \in$ PS;

ANDIF $D_{SO_2} \in$ ZO

THEN $[S]_S \in$ ZO;

ANDIF $D_{SO_2} \in$ PS

THEN $[S]_S \in$ ZO。

The rule model is synthetically formulated as (11).

$$[S]_S = f_{ER}(W_M [S]_M, D_{SO_2}, T_b) \tag{11}$$

5. THE MECHANISM OF INTELLIGENT COORDINATOR

The intelligent coordinator based on fuzzy classification strategy integrates the results of two models as the final prediction. During its designation, the superiority and disadvantage of each model need to be considered so as to make full use of the advantages of each model.

The function of intelligent coordinator is to organically combine the two models via the fuzzy dassification and synthesis. The following is the implementation process.

Firstly, the membership function of each input variable is decided according to the input distribution on variables' ranges. Let U denote the range of input variable x and D denote the sample set of x, so $D \subset U$. Suppose the number of samples in D is N and U is divided as $\{U_1, U_2, \ldots U_L\}$, the number of samples in U_i is N_i. The regions are classified as three classes according to sample number of each region (showed in Fig. 4):

If $N_i/N \geq e_{\max}$, then U_i belongs to class Ⅰ;

If $e_{\min} < N_i/N < e_{\max}$, then U_i belongs to class Ⅱ;

If $N_i/N \leq e_{\min}$, then U_i belongs to class Ⅲ.

Where $e_{\min}$ and $e_{\max}$ are region bounds decided by expert to express different sample numbers in different classes. The maximum and minimum of each class are $a_{1\min}$, $a_{1\max}$, $a_{2\min}$, $a_{2\max}$, $a_{3\min}$, $a_{3\max}$.

The fuzzy discourse domain of x is defined as $\{A_x, A'_x\}$, the logical meaning of A_x is the weight of mathematical model to be dealt with. A'_x is the complement of A_x, which means the weight of expert rule model to be dealt with. The membership function of A_x is trapezoid function (showed in Fig. 4), the formula is

$$m_{A_x}(x) = \begin{cases} \dfrac{x - a_{2\min}}{a_{1\min} - a_{2\min}} & a_{2\min} < x < a_{1\min} \\ 1 & a_{1\min} < x < a_{1\max} \\ \dfrac{a_{2\max} - x}{a_{2\max} - a_{1\max}} & a_{1\max} < x < a_{2\max} \\ 0 & otherwise \end{cases} \tag{12}$$

Then the membership function of A'_x is

$$m_{A'_x} = 1 - m_{A_x} \tag{13}$$

The initial parameters of membership function of input variables are determined by statistical analysis from forepassed production data as follows.

$\{a_{2\min}, a_{1\min}, a_{1\max}, a_{2\max} | D_{SO_2}\} = \{3, 4, 5.5, 6\}$

$\{a_{2\min}, a_{1\min}, a_{1\max}, a_{2\max} | W_M [S]_M\} = \{11, 11.7, 13.2, 14\}$

$\{a_{2\min}, a_{1\min}, a_{1\max}, a_{2\max} | T_b\} = \{150, 250, 450, 500\}$

These parameters are self-adjusted by the information and knowledge from the process acquisition.

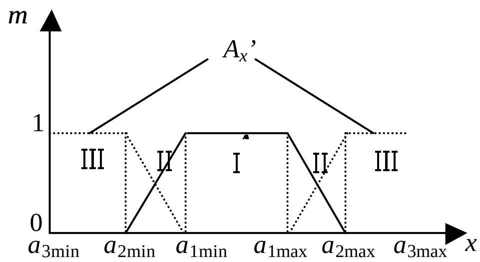

Fig. 4. Fuzzy classification and membership functions of input variables

By fuzzy inference and operation, the intelligent coordinator calculates the final prediction of sulfur in agglomerate. The synthesized membership function of input is calculated by weighted mean method.

$$m_A(x) = \frac{\sum_{i=1}^{3} m_i b_i}{\sum_{i=1}^{3} b_i} \tag{14}$$

where $m_i (i = 1,2,3)$ is the membership function of D_{SO_2}, $W_M [S]_M$ or T_b respectively and $b_i (i = 1,2,3)$ is the weight of each variable decided by experience.

Let f_{MN} and f_{ER} respectively represent the result of mathematical model and expert rule model. The intelligent coordinator computes the prediction by Eq.(16)

$$y = f_{MN} m_A(x) + f_{ER}(1 - m_A(x)) \qquad (15)$$

By this coordinator based on fuzzy operation, the mathematical model take more effect when the process condition is normal and the material balance is reached. Whi1e the process condition is abnormal and the material balance is broken, the feasibility of material balance equation is decreased and the accurate value of sulfur is less precise in mathematical formula. In this case, the result relies more on expert rule model.

6. INDUSTRIAL APPLICATION RESULTS

As expressed in Fig.1 and Eq.(16), this intelligent integrated model composed of mathematical model with NN prediction and exp ert rule model is applied to the sintering process in a Pb-Zn smelting plant in the south of China. Fig.5 is the curves of prediction results, where solid line represents predictive results of model and dotted line represents expected practical data.

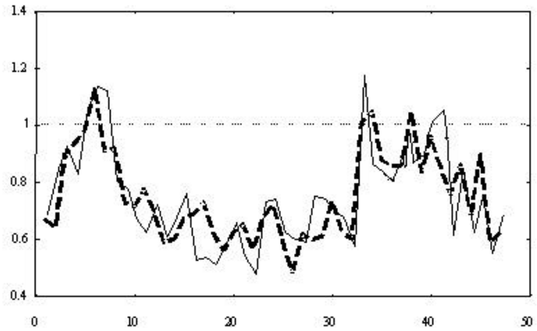

Fig.5 The practical curves of prediction model

Relative mean squared error is calculated as

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\frac{y(k)-\hat{y}(k)}{y(k)}\right)^2} \qquad (16)$$

Where N is the number of predictive samples, $y(k)$ is practical output result and $\hat{y}(k)$ is predicted output.

The practical application results show that this model produces a relative mean squared error of 7.5% and a standard error of 10% in prediction, which is better than expectation taking serious disturbance and system complexity into account, especially comparing with that RMSE of a simple neural network model using BP algorithm is more than 20%. What' s more, this integrated model preferably reflects the changing tendency of sulfur in agglomerate and mathematical relations and empirical knowledge ensure the reliability of results. Therefore, the engineers get profitable instruction by knowing sulfur content in advance from this model for sintering process operation and control. Such outcome had hardly been achieved by previous work about complex Pb-Zn smelting process.

7. CONCLUTION

The intelligent integrated modeling strategy is proposed aiming at the modeling difficulty owing to extreme complexity of plants. The essence of the modeling strategy is to combine existing intelligent technology, such as neural network, fuzzy logic, expert inference and so on, with conventional modeling measure like mechanism analysis to flexibly integrate them into modeling process during which all sorts of data and information of present object is made full use of. The information includes process data, physicochemical knowledge and producing experience. In this paper, an intelligent integrated model combining a mathematical model based on mechanism analysis and NN modeling with expert rule model based on empirical knowledge by an fuzzy coordinator is established to predict sulfur content in agglomerate for smelting process control. The integrating principles contained in fuzzy operation make sure that each model can do its best according to its advantages.

In short, the modeling strategy involves both integration of modeling technology and that of object information. The foregoing integrated model has confirmed its superiority to single modeling method.

REFRENCES

Åström K.J., Anton J.J., Arzen K.E. (1986), Expert Control. *Automatica*, **22(3)**, 277-286

Chen S. and Billings S.A (l992), Neural networks for nonlinear dynamic system modeling and identification. *Int. J Control*, **56(2)**, 3l9-346

Chiu S. (1994), Fuzzy model identification based on cluster estimation. *Journal of Intelligent & Fuzzy Systems*, **2(3)**, 267-278

Hagan M.T. and Menhaj M. (l994), Training feed forward network with the Marquardt algorithm, *IEEE Trans. on neural network*, **5(6),** 989-993

French S. (1995), Uncertainty and imprecision: modeling and analysis, *Journal of operations research society*, **46(1),**70-79

Nikravesh M. (1996), Model identification of nonlinear time variant processes via artificial neural network. *Computers & Chemical Engineering*, **20(11),** 1277~1290

Wu M., Nakano M., She J.H.. (1999), A Model-based Expert Control System for the Leaching Process in Zinc Hydrometallurgy. *Expert Systems with Applications*, **16(1)**, 135-143

Wu M., Shen D.Y., (2000), Expert control based on neural networks and mathematical models for the coal blending process, *Control Theory and Applications. China,* **17(6)**, 868-872

Wang Y.L., Gui W.H., Yang C.H., et al. (2000), Intelligent modeling and optimization on time-sharing power dispatching system for electrolysis process of zinc, *Trans. Nonferrous Met. Soc. China*, **10(4),** 561-565