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Hybrid Model Based Optimal Control for a Metallurgy Process

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Abstract: This paper applies hybrid modeling method based optimal control in industrial process. Hybrid modeling method combines a priori information with a nonlinear residual compensation technique to build a global model which predicts alumina raw pulp slurry quality. Process control is accomplished based on blending expert knowledge with multi-objective hierarchy reasoning approach. Through the coordination of model and controller, the optimal control of blending process is achieved. Application results show that the proposed method can resolve optimization problems of a kind of industrial processes characterized by time delay and multi-constraints.

1. INTRODUCTION

The increased fierce competition over the last few years combined with large alumina price fluctuations has forced most alumina and metallurgy companies to find ways to streamline and optimize plant operations. At the same time, increased computing power combined with improved modeling tools has provided the opportunity to use different modeling technology for generating accurate product quality predictions. Moreover, modeling such complex industrial processes is a complicated procedure and is traditionally done using white box modelling or black box identification (Sjőberg et al., 1995), where white box modelling means that the model is constructed using scientific relations that completely describe the process. The black box identification of making a process model is done by using a standard parametric model is adapted to measured data obtained from the process.

Many white box modelling techniques, so-called first principle, exist for metallurgy processes, such as mass and energy balance, physicochemical reaction and thermodynamic mechanic. However it's very hard to deduce a precise physical formula, no matter its structure or parameter, due to not only the inherent complexity of such process but also the practical production environment. On the other hand, most model-based control strategies (Rohit, 2007; Zhang, 2007) make use of general linear or nonlinear black-box techniques to model the relationship between process input and output variables. This kind of method has the advantage of bypassing the complexity and the uncertainty of the physical systems. However, such models, especially nonlinear ones, may become themselves complex and involve a large number of parameters. Searching for the desired model parameters in a high dimensional model parameter space is prone to local minima and could lead to an inappropriate model. So, a new strategy combining these first principles with general black-box techniques is adopted as a means to trade-off between the complexity and the performance of such complex industrial processes at the supervisory control level.

Generally, in hybrid modeling approach (Bohlin, 2001; Sohlberg, 2003), fundamental knowledge captured from industry process is used to define a prior parametric model with fixed structure derived from either first principle, existing empirical correlation or mathematical transformation, while the unknown part is modeled by a black-box model. Modeling this unknown part is usually much less complicated than modeling the whole process using a black-box model.

The main contribution of hybrid modeling approach (Chen et al., 2004; Li et al., 2004) is as follows. First, this kind of model contains more physical meaning than a total black-box model thanks to the introduction of mechanical knowledge about the process. Second, some inherent problem of black-box technology can be overcame, for instance, the dimension and the feasible region of the parameter space are reduced that can hopefully overcome some identifiability problems, at the same time, the model has better generalization capability than a complete black-box model when the hybrid model structure is appropriate. Last but not least, the whole hybrid model is more suitable to be used in the practical engineering.

In this paper, as the key to the process control success, the hybrid modelling technology is realized successfully in a metallurgy process, alumina blending process control. The control system is composed of a prediction model and an expert controller. The prediction model is employed to forecast raw pulp slurry quality, which consist of mass balance equation and neural network model as estimator for some of the important process parameters as well as compensator of the physical model. The function of controller is to implement optimal raw material ratio setting control, which is based on expert knowledge. Through the coordination between the prediction model and expert controller, the optimal control of the blending process is achieved.

The rest of this paper is devoted to implementation details and explains the benefits derived from such an application in a metallurgy process. The structure of paper is as follows. Section 2 describes the blending process. The control approach existing in practical spot and the new control system proposed in this paper is analyzed in this section. Section 3 focuses on the hybrid prediction model of RPS quality and verifies the model using the practical production data. The expert controller is designed in Section 4. Section 5 shows the practical application results. Section 6 ends with a conclusion.

2. BLENDING PROCESS CONTROL SYSTEM

2.1 Process Description

The goal of alumina production is to extract alumina from the bauxite. This production process is a long and complex production flow, which is composed of many procedures. In such multi-unit production chain, the product of a previous procedure is used as the primary material of the subsequent process, thereby having the direct influence on the following product quality and indirectly impact on the final product. The failure of any node in this long chain has fatal detriment to the overall production system. So, in order to guarantee the final product quality, every production unit has to meet the strict technological requirements. Our research focuses on the first procedure of the alumina production, the blending process (BP). As the first procedure, the significance of BP is obvious. The quality of raw pulp slurry (RPS), product of BP, is pivotal to achieve the whole production success (Zhou, 2004).

In BP, the first step is to send all raw materials to ball mills to grind it for about forty minutes. In actual production, it is impossible to obtain the qualified RPS at the first time due to many issues which will be analyzed later. In order to satisfy the quality requirement, a second mixture or multiple-time mixture is introduced until the requirement is satisfied. Mixture procedures occur in some huge vessels on industrial spot. In the plant where the research was carried out, the matter from ball mill experience a total three-time mixture. Consequently, the practical BP becomes more complex than that in theory and alumina production costs are raised greatly. How to promote the one-time-quality of RPS and shorten the production procedure is a concern of research community and alumina industry (Li, X.B. et al., 2004).

The BP complexity results from many aspects.

First, especially in China, the quality of raw materials can not be guaranteed. Source and ingredients of raw ore frequently change, which cause stable product control difficult.

Second, in BP, the sort of raw material is numerous. The materials include not only necessary ore (bauxite) and chemical matters (lime, and lime stone, caustic soda, coal) but also the product from the other procedures in long alumina production chain such as spent liquor and white residue. Spent liquor is the product of carbonization precipitation process, which is recycled to BP in order to maintain the alkali balance of the whole alumina production system. White residue is a kind of mud residue from the de-silicification process, which is reintroduced to BP in order to prevent loss of alumina as much as possible. The ingredients and flux of these two matters are time-varying, which are influenced by production condition of carbonization and de-silicification procedure. Shortly, BP is impacted by the other units in this production chain.

Third, a large lag time exists in BP which is caused by the process inherent characteristics and delayed access to key measurements. Moreover, this lag-time is a variable changing with different production conditions.

Fourth, many hidden variables and external random disturbs affect the process, which are often impossible to be measured and thus impossible to control.

Last, it should be noted that qualified scopes of RPS technical index are rather minute (fine). Take the most important index, ratio of alumina to silicon (*A/S*) for example, the value should be within the range (4.50, 5.10), that is to say the gap can't exceed 0.60. For such large-scale industrial production, such precision requirements definitely add great control difficulties.

2.2 Quality Indexes and Control Targets

Quality of RPS is characterized by several quality indexes. They are:

Alkali ratio ([*N/R*]). The alkali ratio is the molar concentration ratio of sodium oxide to sum of alumina and ferrous oxide, that is $\frac{[Na_2O]}{[Al_2O_3]+[Fe_2O_3]}$. If the molar concentration of each matter in [*N/R*] is converted to mass, the expression is $\frac{1.645\sum Na_2O}{\sum Al_2O_3+0.6375\sum Fe_2O_3}$.

Calcium ratio ([*C/S*]). The calcium ratio is the molar concentration ratio of calcium oxide to silica, that is $\frac{[CaO]}{[SiO_2]}$. The mass expression converted from molar concentration is $\frac{1.071\sum CaO}{\sum SiO_2}$.

Alumina silica ratio (*A/S*). The alumina silica ratio is the pure mass ration of alumina to silica.

Ferro alumina ratio ([*F/A*]) is the molar concentration ratio of ferric oxide to aluminium oxide, that is $\frac{[Fe_2O_3]}{[Al_2O_3]}$. The mass expression converted is $\frac{0.6375\sum Fe_2O_3}{\sum Al_2O_3}$.

Finally, the water percentage of the raw pulp slurry.

All these indexes should be controlled within certain range. The value range of each index for example is shown in the Table 1. The given value is determined by the technical index of clinker which is the product of the consequent procedure in alumina production and will change periodically with clinker production condition variance.

Table. 1 Value range of index

Index	[*C/S*]	*A/S*	[*F/A*]
Range	1.90~2.10	4.80~5.00	0.077~0.081

Thus, the control task is to determine the ratio setting value of each raw material according to the given quality indexes and accordingly achieve high quality of RPS using obtained ratios.

2.3 Existing control approach

At present, the common control approach in practical production is to establish an approximate mass balance equation of BP using linear programming or empirical formula. The basic feature of this method is to link observations together into some pattern. However, due to the mechanical limitations of BP and large number of the variable involved in system it is hard to set up such formula which can reflect the real system completely. At the same time, in order to alleviate the complexity, the multi-variable problems are usually solved as a less variable one. Besides, the industrial conditions where this research was carried out are much stricter than those considered for the modelling. For all these reasons the process is controlled using empirical knowledge of operate experts as the only strategy.

The human operator on production site determines proper set-point values for control variables of each raw material. This human supervised blending operation with DCS is schematically illustrated in Fig.1.

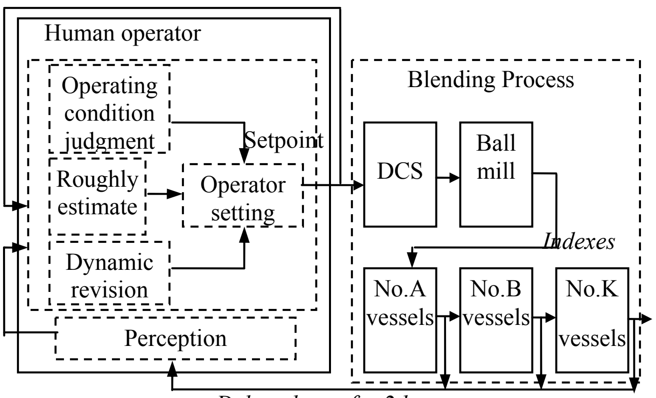

Fig.1. Operation of the DCS controlled BP with human supervision

2.4 New Control Framework

In the new control system, we make good use of all available process information. Firstly, we combine the physical knowledge modeling technology and intelligent technology to set up hybrid prediction model of RPS quality. Secondly, the experience and knowledge of human operator are employed as decision strategy. Accordingly, an expert rule base is set up based on it. The whole control system is illustrated in Fig. 2 and discussed in detail below.

- The physical model based on mass balance is a first-principle model. In this physical model, some important process parameters are obtained by a nonlinear prediction method (Neural Network).
- The physical model can't reflect practical production completely. So, the other forms of knowledge, statistical, qualitative or expert rules are applied to compensate the mechanical knowledge. The residual compensation integration model of physical model fulfils this function, which is integrated to physical model by an expert coordinator.
- A rule based ratio optimization controller is designed to achieve the ratio settings. The rule controller includes a knowledge base and hierarchy reasoning mechanism. In rule database, expert knowledge is divided into several rule groups according to different constraints and practical ratio regulating principle. Such well-organized rule bases facilitate the inference speed. Hierarchical reasoning strategy is designed to infer the optimal ratio of raw material as control setting value.

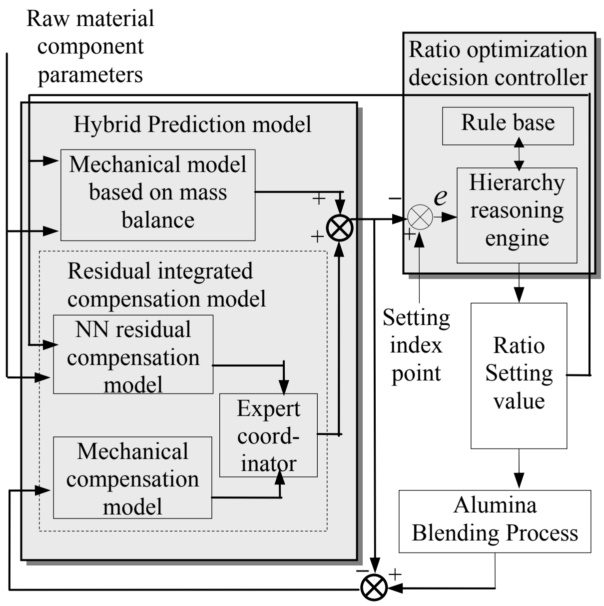

Fig.2. New BP control system scheme proposed

3. HYBRID PREDICTION MODEL OF RPS QUALITY

3.1 Physical Models Embedded with NN

Based on mechanical knowledge of the BP, the physical model is set up according to mass balance theory. Suppose K kinds of raw material are used to produce the raw pulp slurry. Let M_i be the mass of the ith raw material.

The equation of water mass balance can be obtained using the following equation,

$$\hat{H} = \frac{\sum_{i=1}^{K} M_i H_i - H_{Los}}{\sum_{i=1}^{K} M_i} \qquad (1)$$

Where, $\hat{H}$ is the water concentration percentage in RPS, H_i the water content percentage of the *ith* raw material. H_{Los} the water consumed in a chemical reaction which will be depicted later.

The framework of CaO, Na_2O, SiO_2, Fe_2O_3, Al_2O_3 mass balance is

$$\hat{P} = \frac{\sum_{i=1}^{K} M_i P_i}{\sum_{i=1}^{K} M_i - (\sum_{i=1}^{K} M_i H_i - H_{Los})} \qquad (2)$$

Where, $\hat{P}$ is content percentage of the matter P in the dry RPS, P_i the matter P content percentage of the *ith* raw material.

Because some chemical reactions occur in BP, some parameters can't be obtained directly. These parameters in the physical model are calculated as follows.

(1) On production site the measured composition of alkali is Na_2CO_3, in the balance equation of Na_2O the useful content of Na_2CO_3 should be converted to that of Na_2O. The equation is:

$$\hat{N}_{al} = k_{al} \cdot m_{al} \cdot N_{al} \qquad (3)$$

Where k_{al} is conversion coefficient, m_{al} is mass of alkali. N_{al} represents useful Na_2CO_3 content in alkali.

(2) The test method of water in RPS goes as follows: one unit RPS is weighted and dried at 150 ℃. Difference between the wet matter and the dry one is the weight of water. However, in this process a chemical reaction will take place between the lime and water.

$$CaO + H_2O = Ca(OH)_2 \downarrow$$

Calcium hydroxide is the production of this chemical reaction, which consumes some water. That is why, in the equation of water mass balance, the consumed water H_{Los} should be subtracted.

$$H_{Los} = k_{ca} \cdot m_{ca} \cdot C_{ca} \qquad (4)$$

Where, k_{ca} is conversion coefficient. m_{ca} mass of lime. C_{ca} is CaO content percent of lime.

(3) White residue density is an important parameter, but can't be obtained directly. However, it has certain relationship with water content. A linear regression model is used to reveal this relationship based on the least-square method. The deduced equation is

$$\rho_{Si} = \alpha H_{Si} + \beta \qquad (5)$$

Where, $\alpha = -0.0089,\ \beta = 1.9304$.

(4) The NN model of spent liquor density. Spent liquor from carbonization precipitation is a kind of supersaturation solution whose ingredients are rather complex. The unsolvable part is called GUHAN in production. On industrial site, for spent liquor three parameters are measured directly. They are *NT* density (Na^+content in liquid), *AO* density (Al^{3+}content in liquid) and mass of GUHAN. The density of spent liquor is related to *NT* density, *AO* density and mass of GUHAN and this relationship is nonlinear. Owning to the property of function approximation of NN, an NN model of multilayer feedforward network is introduced to describe this relationship as formulated in (6). Levenberg-Marquardt algorithm is adopted as learning strategy, which has fast convergence and can avoid local minimum.

$$\rho_{TM} = f_{NN}(N, A, G) \qquad (6)$$

Where, N represents *NT* density, A is *AO* density, G is mass of GUHAN.

3.2 Intelligent Residual Compensation Models

The BP mechanism in practice is quite different from that in theory. Theoretical mechanisms ignore factors brought by real production environment. In addition, physical model ignores some useful information due to measurement problem. All these make development of a precise physical model difficult. In order to compensate such inevitable errors, neural network (NN) is employed to model the residue of physical model.

In order to simplify the structure of NN, PCA (principal component analysis) is employed to reduce the dimension of input variables of the NN model. Take the calcium oxide compensation model for example. The neural network is a traditional three-layered feedforward one. It receives operating variables, including the amount of bauxite, lime, caustic soda, spent liquid, coal and alkali and the calcium oxide content in the bauxite and caustic soda. The hidden layer has 15 neural nodes. The output of NN is compensation value.

In total 100 sets of chemical analysis results fitting to the sample space are divided into two parts. One part is employed for training, the other for verification. The observed deviations between the physical model and the state variable measurements are used as error signals to the network. The weight factors of the neural network in the hybrid model are determined by minimizing the deviations of the model outputs from the experimental data.

The compensation method of other variables is similar to that of calcium oxide.

3.3 Hybrid Prediction Models

Within the experimental data, the NN model is more precise, but extrapolation capacity is limited. In order to deal with the model residual from sample space, history data are employed to compensate.

Suppose at K time, if the inputs are outside the domain of NN training, the compensation value $\Delta P_G(K)$ is computed like this:

$$\Delta P_G(K) = P_R(K-\tau) - \hat{P}(K-\tau) \qquad (8)$$

Where $P_R(K-\tau)$ and $\hat{P}(K-\tau)$ are state variable measurements and mathematical model prediction of *K-τ* time. τ is the lag time of process and relates to sampling time and number of available ball mills and vessels.

Supposed $\mathcal{S}$ is the domain of the NN model input variables, $\mathcal{X}$ is the input variables. The expert coordinator on line works like this:

Rule1: IF $\mathcal{X} \in \mathcal{S}$ THEN $\Delta P = \Delta P_{NN}$

Rule2: IF $\mathcal{X} \notin \mathcal{S}$ THEN $\Delta P = \Delta P_G$

So the hybrid quality prediction model of RPS is:

$$P = \hat{P} + \Delta P \qquad (9)$$

Where $\hat{P}$ and ΔP are the output of physical model and hybrid residual component model.

3.4 Analysis of the hybrid model precision

The verification result of the proposed model using practical production data is shown in Fig.3.

RMSE (Relative Mean Squared Error) is used to judge the precision of the model, which is defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\frac{y(k)-\hat{y}(k)}{y(k)}\right)^2}\% \qquad (10)$$

Table 2 illustrates the RMSE comparison of *A/S*, [*C/S*], [*F/A*] index value predicted by the physical and hybrid model respectively.

Tab.2 RMSE comparison between physical and hybrid model

	A/S	[C/S]	[F/A]
Physical model	6.20%	8.37%	7.97%
Hybrid model	3.46%	4.71%	5.32%

From the results, we can see that the hybrid model is more precise than the physical one. The practical results, when the proposed model is used in production process, also verify that it is an effective reference for the practical production. Although the proposed model can't give the 100% accurate prediction value, the result is still satisfying and exciting. After all taking serious disturbance and system complexity into account, the performance of the model provides the good basis for the system controller.

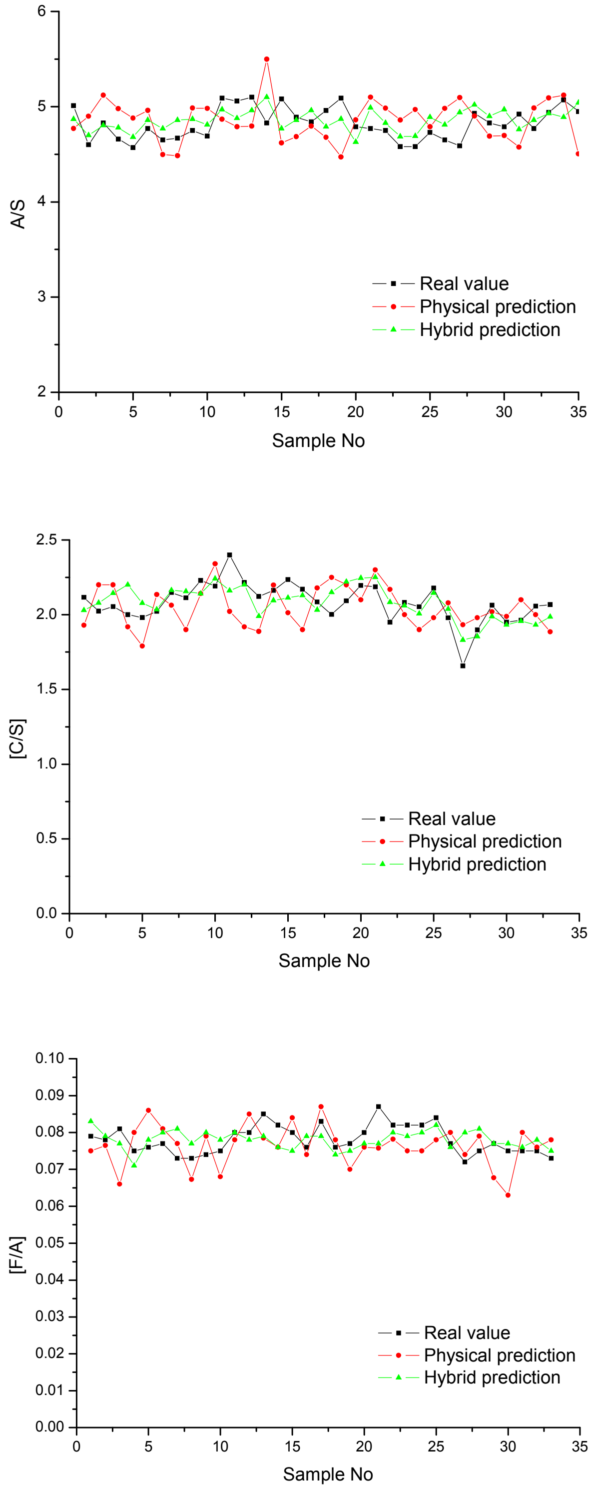

Fig.3 Comparison between the predictive values of physical model and hybrid model

4. RATIO OPTIMIZATION SETTING

The optimization controller of the ratio setting adopts the multi-object hierarchy reasoning strategy to realize the ratio optimization setting control. The ratio setting value is deduced by quality predictions and the given indexes.

4.1 BP Knowledge Base

The amount of BP expert knowledge information is so large due to the facts such as multi-variable, multi-constraint involved in the process and coupling between different variables and so on. All these make BP knowledge rules extremely diverse. So, a well-structured expert system that can be utilized easily and practically can promote the system performance greatly.

In practice, the principle of human operator regulating ratio follows such criterion, "the index A/S requires more attention, while the other indexes are regulated in sequence". Accordingly, a quality effective coefficient (QEC) is assigned to each index to indicate the different importance of each index in the regulating process. The more important the index, the smaller the QEC, and vice versa. Thus the QEC of A/S is smallest, the value of which is 1. The QEC value of [*C/S*], [*N/R*], [*F/A*] and water is 2,3,4,5 respectively. Consequently, according to QEC the BP knowledge is divided into the corresponding knowledge group. In each group, the corresponding rules are arranged by the priority level. The rules which are invoked more often have higher priority level. Such rule organization architecture can speed up reference engine greatly.

The general expression of rules is like:

$$Rule^i : R(RGNo, RNo, CList, ConcNo)$$

Where, $Rule^i$ represents the corresponding knowledge group whose QEC is *i*. *RGNo* is group number. *RNo* is rule number in a knowledge group and is arranged by rule density. *CList* is a table of conditions (TC). Each TC is of form: "((CNO_i,Tag_i), $i=1,2,\ldots,n$)".Where, Tag_i is a tag which indicates whether this rule is the last one. If the rule is last one, the value of Tag_i is 1, else 0. *ConcNo* is result number. Each number matches a corresponding expert operating action, all of which are stored in result database.

For example: R^1： IF {*A/S* qualified,0} AND IF {[*C/S*] qualified,0} AND IF {[*N/R*] qualified,0} AND IF {[*F/A*] qualified,1} THEN {0101}

R^1 is the knowledge group used to regulate *A/S*.

0101 is the result number. The reference engine invokes corresponding action from the result database. In this case, the action represented by 0101 is that there is no need to regulate ratio.

4.2 Hierarchical Inference Strategy

The inputs of ratio optimization reference model(RORM) are the difference between the outputs of quality prediction model and index setting value which are denoted by $E_{A/S}$, $E_{[C/S]}$, $E_{[N/R]}$, $E_{[F/A]}$, E_H respectively.

Hierarchical inference strategy is adopted in the RORM. The reasoning procedure is divided into several sub-reasoning procedures according to object constraints. Suppose E_i is the difference between the prediction value of *i*th index and its set point. M_i (>0), L_i (>0) are technical parameters relating to the *i*th index（$M_i < L_i$）in the production process. P_{2i}, P_{1i} are the ratio regulation step length of *i*th level, $P_{2i}>P_{1i}$. The value of step length is decided by the practical operation experience.

The *i*th level optimization inference mechanism is as follows:

Step1: Judge whether the *i*th level reasoning is the last level reasoning. If yes, the reasoning is ended and the current value of the ratio is outputted; else, go to Step 2.

Step2: IF $|E_i| \le M_i$, THEN go to step 6; ELSE go to the Step3.

Step3: IF $|E_i| > L_i$, THEN regulating ratio by P_{2i} step length, then go to the Step 5; ELSE go to Step 4.

Step4: IF $M_i < |E_i| \le L_i$, THEN regulating ratio by P_{1i} step length.

Step5: Recalculate the prediction value by inputting new calculated ratio. Then go to Step2.

Step6: Go to the *i*++th level reasoning.

The inference progress can be illustrated by Figure 4.

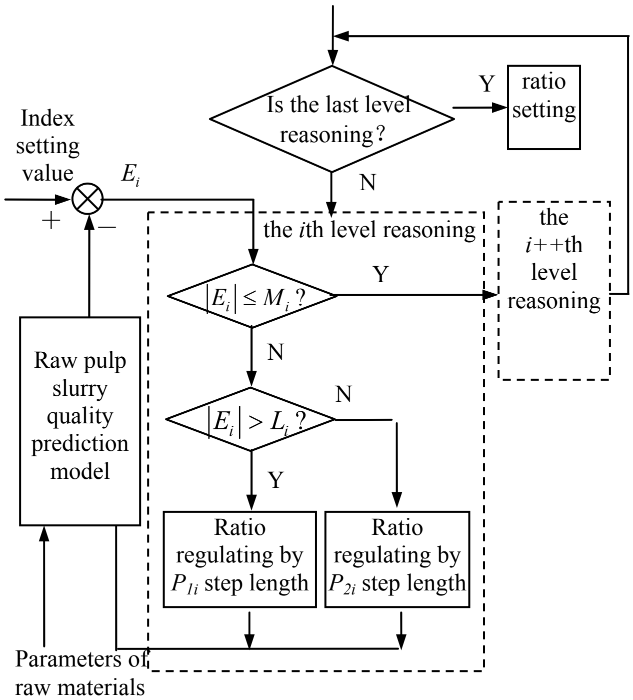

Fig. 4. Multi-objects hierarchical reasoning diagram

5. INDUSTRIAL APPLICATIONS

The proposed control system of BP has been put into service in Zhongzhou Alumina Refinery which is located in Henan province, China in 2004. It is an important part for the optimal control of BP in alumina production. Control software is implemented by Visual C++ program language and is executed on an expert optimization computer (EOC). EOC exchanges the information with six real-time monitor and control computers (RMCCs) by OPC technology. RMCCs send the ratio setting value to distributed control system (DCS) by DH+ (Data Highway Plus) Network. The automatic feed control is realized.

In order to show the system performance, quantitative analysis is done. One work day data (24 hours) was analyzed to show the validity thanks to control system implementation. Due to page limitation, data are not shown in the paper.

A judgment index, shooting percentage (SP), is introduced to verify the performance of the result, which indicates the fluctuation of the practical results.

$r_i(i=1,2,...,n)$ is the sample from A vessels. $\bar{r}$ is supposed to be the average value of all samples r_i. The difference between each sample and $\bar{r}$ is $\mu_i = r_i - \bar{r}\,(i=1,2,...,n)$.

The SP is defined as: $P = \frac{m}{n} \times 100\%$ .Where, m is the sample number which satisfies $|\mu_i| \le \varepsilon$, ε is a technical parameter depending on specific application. P denotes the fluctuation degree of production index. A larger P means that more data points fall into [$\bar{r}$ - μ_i, $\bar{r}$ + μ_i], more smooth control result, verse vice.

In this case, according to practical quality requirements, $\varepsilon_{[C/S]}, \varepsilon_{A/S}, \varepsilon_{[F/A]}$ is fixed to±0.15, ±0.15, ±0.005 respectively. Thus, comparison of $P_{[C/S]}$, $P_{A/S}$, $P_{[F/A]}$ before and after the new system implementation is shown in Tab.3.

Tab. 3 Indices comparison before and after the new system implementation

	After	before
$P_{[C/S]}$	83.72%	48.48%
$P_{A/S}$	77%	45.45%
$P_{[F/A]}$	93.93%	48.48%

From table 3, we can see that product quality index became much better after the new system implementation than before. The result reveals the fact that the proposed control system can eliminate the bad influence caused by system inherent delay.

6. CONCLUSION

BP is a classical complex industrial process with a large lag-time, multi-variable, uncertainty and multi-constraint. As the foundation of successful system control, the hybrid modelling technology shows the amazing power. The paper takes advantage of hybrid model technology to set up RPS quality prediction model. Thanks to its desired precision, this model effectively eliminates the awful influence caused by inherent process delay, while which can't be achieved by human operator. Based on trustworthy predictions, an expert controller which mimics human inference process is developed to optimize ratio setting value of input raw material. A well-constructed rule base and novel hierarchical reasoning mechanism promote system performance greatly. The coordination of two important parts (model & controller) finally brings the success. Application results prove this success powerfully. The method proposed in this paper provides an available, feasible and general framework for goal-directed optimization control of such complex industrial process.

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