Multiple Model Predictive Control of Component Content in Rare Earth Extraction Process

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***Abstract*—Aiming at the complicated characteristic of rare earth extraction process and combining the material balance model, a multiple models modeling and control method is proposed. Based on the data collected in an industrial field, an improved subtractive clustering algorithm is employed to obtain steady operation points for the process; the recuresive least squares algorithm is adopted to identify submodel parameters and establish multiple linear models. According to the model switching index, an online optimal predictive model is obtained. And the efficiency of the model is verified by taking a certain rare earth company extraction as an example. In the end, generalized predictive controller of the corresponding sub-model is designed, so that component content is controlled in real time and accurately. Simulation results show the effectiveness of the method above.**

***Index Terms*—rare earth extraction process, complicated characteristic, multiple models, generalized predictive control**

I. Introduction

There are many controlled parameters Iin rare earth extraction process, among which purity of rare earth is the foremost. It's indispensable to measure the component content. However, the extraction process has complexities like strongly nonlinear, multivariable, strong decoupling, delay and time variance between component content and solvent flow-rate, material liquid flow-rate and hydrochloric acid flow-rate. Component content also varies with the disturbances of solvent saponification degree and feed-in compositions and so on[1]. And it's hard to be measured online and get optimal control with conventional modeling and control methods.

The present chief methods for component content online measurement in rare earth extraction process include UV-VIS, FIA, LaF_3 ISE, Isotopic XRF and so on. Because of high cost of the equipments, low reliability and stability, their usage in industry are generally limited. The soft sensor technology has many advantages such as precisenss, reliability, economy dynamic fast response, easy to realize the preset control in the outcome product purity and so on. The soft sensor method provides a new way to the online measurement of component content in rare earth extraction process[2]. In[3], a soft sensor method was proposed for the measurement of component content with hybrid models.However, the dynamic characteristics of rare earth extraction process can't be fully reflected for limitation of static analysis.With the development of neural network, it has been widely applied in the modeling of nonlinear system. In[4], a modeling method using neural network was proposed for rare earth extraction process, and with the limitation of data sampled, all working conditions could not be covered by training results with this method, which resulted in low predictive accuracy and poor training effect. To solve the problem above, in[2], an intelligent optimal control strategy was provided by combining the technologies based on soft sensor and CBR(case-based reasoning). But the strategies are still based on neural network.

The multiple model approach is an efficient and simple framework for identifying and modeling of complex nonlinear process[5]. In[6], a soft sensor method with multiple model was propsed. It established a model set with 5 extraction stages to measure component content online, but it would lead to redundant model, which not only increased the number of models, caused large calculation, but also reduced the precision of the model without optimal control.

Manuscript received Sep. 8, 2011; revised. Oct. 20, 2011; accepted Nov. 5, 2011.

doi:10.4304/jcp.7.10.2557-2563

In industrial applications, model predictive control(MPC), an optimization model-based controller, has achieved great successes, and most of commercailly avaiable MPC products have utilized linear model[7]. Nevertheless, industrial processes are nonlinear and operate over a broad range of operating conditions. On the other hand, an important advantage of multiple model approach is that existing analysis and synthesis tools for linear systems can easily be adapted to this class of models at the cost of very little modification. Therefore, many efforts were put in development and application of multiple model/controller solutions within the MPC field. It has been reported in literatures that the selection of proper number of models have shown to be an important issue[7, 8, 9].

This work is mainly focused on the difficulty of modeling and control about component content in rare earth extraction process. Multiple linear models with only one extraction stage at monitoring point are established to reduce the number of models and the quantity of calculation, and generalized predictive controller has been developed by using multiple models running in series to cope with whole component content varies. Fistly, by using the improved subtractive clustering algorithm, the steady operation points are obtained. Secondly, recursive least squares algorithm is adopted to identify model parameters by using the data in an industrial field and the multiple linear models are built. Then model switching index is designed to choose the optimal model and the efficiency is verified. Finally, when the predictive value of component content doesn't satisfy the requirement, the outputs of controllers are adjusted so as to ensure quality of the outlet product. The good accuracy performance obtained with the designed soft sensors and controllers shows that the effectiveness of the proposed method in modeling and control for rare earth extraction process. In addition, the problem of large time-delay in the process is also solved.

II. DESCRIPTION OF RARE EARTH EXTRACTION PROCESS

Factional extraction processes are generally adopted in industry for the separation of rare earth, because two kinds of high purity, high recovery rate products can be obtained at the same time for the separation of A, B component, where A is easy extracted component and B is hard extraction component, the two component A and B extraction procedd is shown in Fig.1.

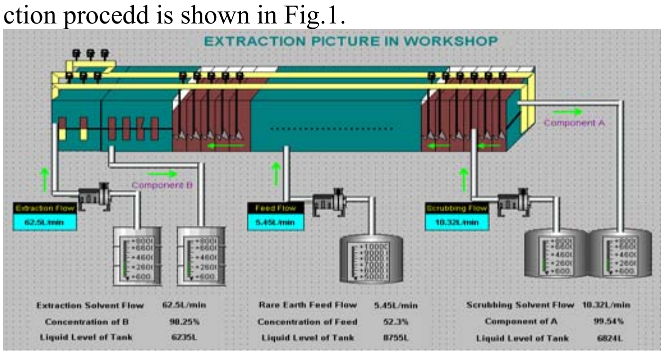

Fig. 1 Picture of rare earth countercurrent extraction process

As shown in Fig.1, the left side is extraction sections composed of n stage mix-clarifiers and the right side is the scrubbing sections composed of m stage mix-clarifiers. In each stage, there is an agitator in each mixer and a flowmeter in tank respectively.

In Fig.1, the extraction solvent flow rate u_1 is added into the 1^{st} stage mix-clarifier, which is flowing from left to right through the agitator in mixer. Simultaneously the rare earth feed flow rare u_2 containing the element to be extracted is added into the n^{th} stage mix-clarifier, which is flowing from right to left. At the same time, the flow rate of scrubbing solvent u_3 is added into the extraction process at the $(n+m)^{th}$ stage, flowing from right to left ang joining the rare earth feed at the n^{th} stage. Then, in extraction section, because the istribution ratio is different between organic phase and aqueous phase among elements, more easily extraction component A and less hard extraction component B can be obtained and entered into the organic phase. So, in scrubbing section, through controlling the scrubbing condition, easily extraction component A can be obtained far more than hardly extraction component B, which means A and B can be separated well. Finally, repeating the exchanging and scrubbing in each stage, product B with the purity of Y_B can be obtained at the aqueous phase outlet in extraction section, while product A with the purity of Y_A at the organic phase outlet in scrubbing section.

The simplified schematic diagram of rare earth extraction process is shown in Fig.2, where u_1 is the flow rate of extraction solvent, u_2 is the flow rate of rare earth feed, u_3 is the flow rate of scrubbing solvent, $x_{i,F}$ is the concentration of rare earth feed, $z_{i,j}$, $x_{i,j}(j = 1, \ldots, n+m)$are the concentration of the i^{th} component at organic phase and aqueous phase respectively. Y_A is the purity of A and Y_B is the purity of B. Similarly, $Y_{A,k}$ is the organic phase content A at monitoring point in scrubbing section, and $Y_{B,k}$ is the aqueous phase content B at monitoring point in extraction section.

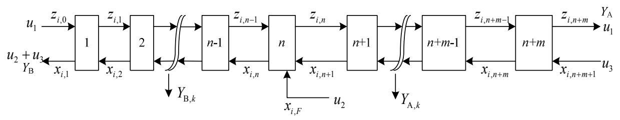

Fig.2 Schematic diagram of rare earth countercurrent extraction process

In order to improve the purity of the extraction product, dozens even hundreds of stages are built in the extraction process. So, it often takes a long-time delay(from several hours to twenty hours) for the control variables, such as rare earth feed, extraction solvent and scrubbing solvent, to adjust product purity. Therefore, process monitoring points have to be set near the outlet of the stage from5th to 25th stage.Then, at each monitoring point, $Y_{A,k}$ and $Y_{B,k}$ should be measured and controlled to obtain the satisfactory products, i.e. Y_A and Y_B. Unfortunately, in practice $Y_{A,k}$ and $Y_{B,k}$ can not implement the real time measurement. To solve these problem above, a multiple model method is proposed.

III. MODELING OF RARE EARTH EXTRACTION PROCESS

A. An Improved Subtractive Clustering Algorithm

Rare earth extraction is a nonlinear process. So it's most important to choose the best operation points and establish the local linear model to approximate the output of nonlinear system above. Clustering is a kind of method which divides a sample set without any label into seveal subsets by the rules. It makes similar sample belong to the same group and different sample belong to different groups. In[10], a sort of subtractive clustering algorithm was introduced, which need not give number of clustering in advance, and can put up unsupervised learning with low calculation and fast clustering. Compared with Fuzzy C-Means(FCM) clustering algorithm, the algorithm in[10] can avoid bad clustering result and local optimum caused by the unsuitable ininial parameters(cluster number and cluster center) in FCM. However, it can produce redundant cluster centers. By analying this problem in the algorithm, it has been found that data density satisfying $D_j^c \le 0$ is one of the important reasons to lead such question. To solve this problem, an improved algorithm which can adjust data density to satisfy $D_j^c \le \xi$ (ξ is a positive constant) is presented. Compared with the orginal method, the improved clustering algorithm above can avoid redundant cluster centers and reduce calculation. Based on the improved subtractive clustering algorithm, cluster centers or steady operations of rare earth extraction process can be obtained.

In multiple model modelling process, the main problem is to determine the number of submodel, ie. the cluster number n. Based on describing all working conditions, the cluster number n should be designed as small as possible. Smaller cluster numbers mean reduction of calculation and system stability when switching among submodels occurs frequently. So, the cluster number n has the following index function:

$$J_{\mathrm{m}} = \sum_{i=1}^{N}\sum_{j=1}^{n} \mu_{ij}^2 \left\| X_i - X_j^c \right\|^2 \qquad (1)$$

where N is the number of sampled data, n is the cluster numbers, $X_i \in R^q$ is the i^{th} sampled data input with $X_i = [u_{1i}, u_{2i}, u_{3i}, x_{i,\mathrm{F}}]^{\mathrm{T}}$, u_{1i}, u_{2i}, u_{3i} are the i^{th} flow rate of extraction solvent, rare earth feed and scrubbing solvent at the aqueous phase respectively, $x_{i,\mathrm{F}}$ is the concentration of rare earth feed corresponding to the i^{th} flow rate. Clearly, rare earth extraction process is a four inputs system. In addition, $X_j^c \in R^q$ is the j^{th} cluster center with $X_j^c = [u_{1j}^c, u_{2j}^c, u_{3j}^c, x_{i,F}^c]^{\mathrm{T}}$,μ_{ij} is the membership of the i^{th} sampled data at the j^{th} clustering. Like the definition of membership function at fuzzy logic, μ_{ij} is defined as:

$$\mu_{ij} = \frac{\exp\left(-\frac{1}{2}\left\|X_i - X_j^c\right\|^2 \Big/ \sigma^2\right)}{\sum_{k=1}^{n}\exp\left(-\frac{1}{2}\left\|X_i - X_k^c\right\|^2 \Big/ \sigma^2\right)} \qquad (2)$$

In this paper, the improved subtractive clustering algorithm above was used to classify sampled data and clustering effect was evaluated by index function J_{m}:

Step 1: Set initial parameter $\delta_a = \delta_{\min}$ and choose step value($\varepsilon > 0$);

Step 2: Calculate sampled data density:

$$D_i = \sum_{i=1}^{n} \exp\left(-\left\|X_i - X_j\right\| / \left(\delta_a/2\right)^2\right) \qquad (3)$$

Step 3: Set the maximum density $D_1^c = \max D_i$ and choose the first cluster center $X_1^c = X_i \mid_{\max D_i}$;

Step 4: Choose $\delta_b = 1.5\delta_a$ and update data density:

$$D_i^c = D_i^c - D_1^c \exp\left(-\left\|X_i - X_1^c\right\| / \left(\delta_b/2\right)^2\right), \ \left(i = 1,\cdots,N\right) \qquad (4)$$

Step 5: Repeat step 3 and step 4 until $D_j^c \le \xi$, and obtain the j^{th} cluster center $X_j^c \left(j = 2,\cdots,n\right)$;

with: n is cluster center numbers and staisfy $n < N$

Step 6: Calculate the $k^{th}\left(k > 1\right)$ cluster index J_{m} and update $\delta_a = \delta_a + \varepsilon$, if $\delta_a \in \left[\delta_{\min} \quad \delta_{\max}\right]$, then repeat steps 2 to 5;

Step 7: Set $J_m = J_m^k \left(k = 1,\cdots,K\right)$; get cluster numbers n and cluster centers $X_l^c \left(l = 1,\cdots,n\right)$ to classify sampled data corresponding to J_m , and the corresponding data set Ω_l is obtained by using the nearest-neighbour rule.

B. The Dynamic Model Establishing

Around the working point or the clustering center obtained above, considering the characteristics of rare earth extraction process, in every extractor it contains material balance and heat balance, etc. Here material balance can describe the main dynamic characteristics of all process. So the following concentraction dynamic equilibrium relationship is constructed in the j^{th} stage at the aqueous phase of the i^{th} component:

$$\begin{aligned}\frac{\mathrm{d}x_{i,1}}{\mathrm{d}t} = \frac{1}{R_j}[&(u_2 + u_3)x_{i,j+1}(t-\tau) + u_1 D_{i,j-1}x_{i,j-1}(t-\tau) \\ &- (u_2 + u_3)x_{i,j} - u_1 D_{i,j}x_{i,j}]\end{aligned} \qquad (5)$$

where u_1, u_2, u_3 are extraction solvent flow, rare earth feed flow at the aqueous phase and scrubbing flow at the aqueous phase respectively. When j = 1, n+m, $x_{i,0}(t\text{-}\tau) = x_{i,0}$, $x_{i,n+m+1}(t\text{-}\tau) = x_{i,n+m+1}$are all known. When $j > n$, $u_2 = 0$. Here R_j is the holding volume, τ is the lagging time, $D_{i,j}$ is the distribution cofficient between the organic phase and the aqueous phase.

Because of the complication of the whole extraction process, the assumption, which whole extraction process is in the equilibrium state, is made. So the monitoring point is established at the l^{th} stage as in Fig.3 below.

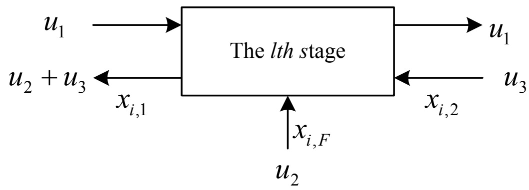

Fig.3 The diagram of component content monitoring point at the lth stage

In order to detect component purity at the monitoring point, according to the concentration dynamic equilibrium relationship described in(5), the relationship of i^{th} component at the aqueous phase in the l^{th} stage is established.

$$\frac{\mathrm{d}x_{i,1}}{\mathrm{d}t}=\frac{1}{R_1}[u_3x_{i,2}(t-\tau)+u_2x_{i,F}+u_1D_{i,0}x_{i,0}(t-\tau) \\ -u_1D_{i,1}x_{i,1}-(u_2+u_3)x_{i,1}] \quad (6)$$

where $x_{i,0}(t\text{-}\tau) = x_{i,0}$, $x_{i,2}(t\text{-}\tau) = x_{i,2}$, are known.

From(6), it can be seen that it's a nonlinear equation. So, at the operation point $E=(x_{i,2}^e, x_{i,1}^e, x_{i,0}^e, u_1^e, u_2^e, u_3^e)$, it has:

$$\frac{\mathrm{d}x_{i,1}^e}{\mathrm{d}t}=f[x_{i,2}^e,x_{i,1}^e,x_{i,0}^e,u_1^e,u_2^e,u_3^e]=0 \quad (7)$$

Then, transforming the operation point in (6) to origin and apply Taylor linear expansion method, the local linear model of i^{th} stage is obtained as:

$$\frac{\mathrm{d}x_{i,1}}{\mathrm{d}t}=\frac{1}{R_1}[(u_2^e+u_3^e)x_{i,2}(t-\tau)+D_{i,1}u_1^ex_{i,0}(t-\tau) \\ -(D_{i,1}u_1^e+u_2^e+u_3^e)x_{i,1}+(x_{i,2}^e-x_{i,1}^e)u_2 \\ +(x_{i,2}^e-x_{i,1}^e)u_3-(D_{i,1}x_{i,1}^e-D_{i,0}x_{i,0}^e)u_1] \quad (8)$$

Discretize (8), it can be obtained as follows:

$$\mathbf{x}_i(k+1)=\mathbf{A}x_i(k)+\mathbf{Bu}(k)+\mathbf{Dv}(k) \quad (9)$$

where $\mathbf{u}(k)=[u_1(k),\ u_2(k),\ u_3(k)]^{\mathrm{T}}$is the input vector, $\mathbf{x_i}(k)=x_{i,1}(k)$ is the concentration state vector, and $v(k)=x_{i,F}(k)$ is the disturbance vector. Here $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{D}$ are model parameters matries.

Then system output is

$$\mathbf{y_i}(k)=\mathbf{Cx_i}(k) \quad (10)$$

where $\mathbf{C}$ is parameter matrix and $\mathbf{y_i}(k)=y_{i,l}(k)$.

Based on(9) and (10), the relationship between $\boldsymbol{u}$ and $\boldsymbol{y}$ is concluded as following:

$$\mathbf{y}(k+1)=\mathbf{Ay}(k)+\mathbf{Gu}(k)+\mathbf{Hv}(k) \quad (11)$$

where $\mathbf{A}$, $\mathbf{G}$ and $\mathbf{H}$ are all undetermined coefficient matrixes.

Based on(11), it can get

$$\mathbf{y}(k+1)=\boldsymbol{\theta}^{\mathrm{T}}\boldsymbol{\varphi}(k) \quad (12)$$

where $\boldsymbol{\theta}=[\mathbf{A},\ \mathbf{G},\ \mathbf{H}]^{\mathrm{T}}$, $\boldsymbol{\varphi}(k)=[\mathbf{y}(k)^{\mathrm{T}},\ \mathbf{u}(k)^{\mathrm{T}},\ \mathbf{v}(k)^{\mathrm{T}}]$. With the system state observed, $\mathbf{y}(k)$ and $\boldsymbol{\varphi}(k)$ in(12) are obtained and $\boldsymbol{\theta}$ is identified by using least-squares identification method.

Model described in(12) is only applied for the condition that is around the special operation point. When it has great changes in system running environment, identifying the parameters are so hard to track practical changes that the model is inaccurate. Through expanding the nonlinear system around multiple operation points and using local linear models established above to approach nonlinear system, dynamic model which is approximate to the practical system can be obtained. Therefore, rare earth extraction process is expanded around different operation points and the system is described with n input-output models I_1, I_2, …, I_n. The discrete local linear model around each operation point is

$$I_l:\ \mathbf{y}^l(k+1)=\boldsymbol{\theta}_l^{\mathrm{T}}\boldsymbol{\varphi}(k),\ l=1,\cdots,n \quad (13)$$

where $\theta_l=[\mathbf{A}^l,\mathbf{G}^l,\ \mathbf{H}^l]^{\mathrm{T}}$ is parameter matrix around the 1^{th} operation point, and $\boldsymbol{\varphi}(k)$ is a matrix composed of input –output data.

According to (13), and combined with the rare earth contercurrent extraction process described in Fig.3, the relationship between component purity y at monitoring point and input u is

$$I_l:\ y(k+1)=-a_1^ly(k)-a_2^ly(k-1)+g_1^lu_1(k) \\ +g_2^lu_2(k)+g_3^lu_3(k)+h_1^lx_F(k) \quad (14) \\ =\theta_l^{\mathrm{T}}\phi(k) \qquad (l=1,\cdots,n)$$

where $\theta_l^{\mathrm{T}}=[a_1^l,a_2^l,g_1^l,g_2^l,g_3^l,h_1^l]^{\mathrm{T}}$ is a parameter vector of the l^{th} model and$\varphi(k)$ = [-$y(k)$, -$y(k$-1), $u_1(k)$, $u_2(k)$, $u_3(k)$, $x_{i,F}(k)$]$^{\mathrm{T}}$.

So, using improved subtractive clustering algorithm above, cluster center X_l^c is obtained as operation point of local linear model, which is steady operation point in practical system. The initial parameters θ_l^o of local are identified with the cluster data set Ω_l and recursive least-square identification method.

C. Model Switching

Modeling switching is a kind of scheduling mechanism in multiple models modeling method. The switching index is chosen according to the factors like practical physiacl object, control accuracy, etc.

Considering the rare earth countercurrent extraction process introduced in this paper, model structure adopts the form of multiple models in(14). Each local linear model has the same structure but the different initial parameters. At every sampling time, according to the switching index, only one local model I_l is selected out to be the optimal model to approximate to the system. To the switching index, different forms have great influence on modeling accuracy and model switching times. In this paper, the switching index function is designed according to the accumulation of the identified error among local models, which has integral property, as

$$J_l(k)=\sum_{j=1}^{k}\beta(j)^{(k-j)}\left|y(k)-\hat{y}_l(k)\right| \quad (15)$$

where $y(k)$ is the real output, $y_l(k)$ is the l^{th} model output, and $0<\beta<1$ is the weighted factor.

The switching index in (15) evaluates the matching degree between each submodel and the system by comparing with current error and historical error. It means the less switching index value is, the more matching degree is. Therefore, the multiple models based on local linear model can be represented as

$$\hat{y}_l(k+1)=\sum_{i=1}^{n}\alpha(J_l)\hat{\theta}_l^{\mathrm{T}}(k)\phi(k) \quad (16)$$

with

$$\alpha(J_l)=\begin{cases}1, \text{if } l=\arg\ \min J_j, j=1,\cdots,n\\0, \text{others}\end{cases}$$

When there are too many submodels, the above model established exists an obvious problem. The matching degree between each submodel and the real system in sequence will lead to huge calculation, which influences the real –time monitoring/controlling. So, the multiple models set must be optimized. Firstly, the established multiple models set is divided into two regions by usage frequency, some of which with higher usage frequency belongs to sensitive region, others are non-sensitive region. To the models in sensitive region, their outputs are computed each time. To the models in non-sensitive region, when the error of the models in sensitive region is more than the threshold designed before, their outputs will be computed. Compared with the past multiple model set, it need not calculate each submodel output in sequence, which causes the calculation reduced.

D. *Verification of Model*

In order to verify the effectiveness of the proposed online prediction method about rare earth extraction component content based on multiple linear models, the real industrial data from a company extracted product yttrium is used to test the model. Based on the model, the element component purity at monitoring point in sensitive stage is measured online. If its purity doesn't meet requirement, by adjusting the flow rate of extraction solvent, rare earth feed and scrubbing solvent in time, the purity at monitoring point is controlled in a reasonable region and the quality of outlet product is guaranteed.

In this paper, 150 groups of real industrial effective data are obtained at monitoring point. Firstly, through the improved subtractive clustering algorithm above, 100 groups of sampled data are devided to four groups and the cluster centers are regarded as operation points as showen in TABLEI. Secondly, in each group, the local linear model is identified off-line by using the corresponding data. Then four models of element component content are obtained, which are shown as model 1~model 4. At last, another 50 groups of ampled data are adopted to test the models. According to the introduced modeling method above, choosing(15) as switching index function, when $\beta = 0.55$, doing simulation with MATLAB, the last result is shown in Fig.4 and Fig.5, respectively.

Compared with the simulated results and defined the following errors: maximum positive error(MPE), maximum negative error(MNE), robust mean square error(RMS E), the errors in two stages of model fitting and model testing are analyed. The result is shown in TABLE II.

From Fig.4 and TABLE II, 100 groups of data are used for the identification of initial models, and the model output error is larger because the model is optimized constantly. Then the other 50 groups of data are used for testing the last optimal model, result shows that the output error is less than before. From the switching curve in Fig.5, it can be seen that condition changes mainly at point 2 and point 3, so the multiple linear models are switched between model 2 and model 3.

TABLE I.
STEADY OPERATION POINTS

	Input Variables(u_1, u_2, u_3)	*Feed Concentration*(x_F)
Point 1	*(73.88, 6.82, 11.30)*	*0.505*
Point 2	*(26.1, 2.50, 3.88)*	*0.529*
Point 3	*(40.30, 3.50, 6.21)*	*0.529*
Point 4	*(55.47, 5.40, 8.49)*	*0.481*

Model 1 ~ Model 4:

$$\begin{cases} y(k+1)=0.0707\ y(k)-0.1067\ y(k-1)+0.0509\ u_1(k)\\ \qquad -0.1507\ u_2(k)-0.2620\ u_3(k)+1.1947\ x_F(k)\\ y(k+1)=0.2649\ y(k)-0.2509\ y(k-1)+0.1102\ u_1(k)\\ \qquad -0.2307\ u_2(k)-0.5622\ u_3(k)+1.2366\ x_F(k)\\ y(k+1)=0.4448\ y(k)-0.0124\ y(k-1)+0.1111\ u_1(k)\\ \qquad -0.2660\ u_2(k)-0.5533\ u_3(k)+0.7552\ x_F(k)\\ y(k+1)=0.1372\ y(k)+0.0648\ y(k-1)+0.0676\ u_1(k)\\ \qquad -0.1592\ u_2(k)-0.3404\ u_3(k)+1.1038\ x_F(k) \end{cases}$$

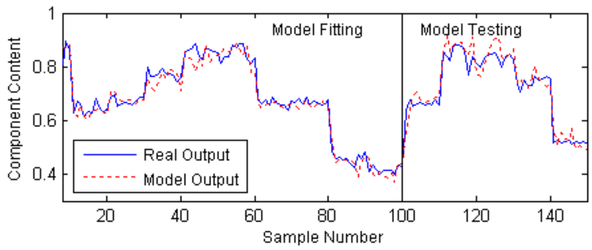

Fig.4 Curves between multiple linear models and real output

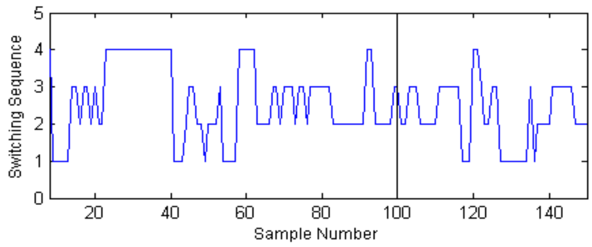

Fig.5 Switching curve of multiple linear models

TABLE II.
MODEL ERROR PERFORMANCE ANALYSIS

	MPE	*MNE*	*RMSE*
Model fitting	*0.1011*	*0.0639*	*0.0281*
Model testing	*0.0397*	*0.0785*	*0.0299*

IV. MULTIPLE MODELS PREDICTIVE CONTROLLER

According to the description in III, the online estimation and real-time monitoring of element component content are realized with the model obtained. When the component content at monitoring point doesn't meet objective value, based on the multiple linear models above and combined with the characteristics of Generalized Predictive Control(CPC)algorithm using CARIMA(Controlled Auto-aggressive Integral Moving Average) model, a Multiple

Models GPC(MMGPC) is designed to adjust control variables to satisfy the requirement fastly.Depending on its historical dynamic information, a MMGPC can predict the control variable, which sloves the problem of large time-delay in rare earth extraction process to some extent.

Model 1 ~ Model 4 are optimized using the sample data which are selected in an industry field. Then, taking controlling scrubbing solvent u_3 as an example, GPC C3 is designed as following.

C3:

$$\begin{cases} y(k)-0.8519\,y(k-1)-0.1633\,y(k-2)+0.0152\,y(k-3) \\ \qquad =-0.2887\,\Delta u_3(k-1) \\ y(k)-1.6020\,y(k-1)+0.6473\,y(k-2)-0.0453\,y(k-3) \\ \qquad =-0.4493\,\Delta u_3(k-1) \\ y(k)-1.2033\,y(k-1)+0.4501\,y(k-2)-0.2468\,y(k-3) \\ \qquad =-0.5339\,\Delta u_3(k-1) \\ y(k)-1.1345\,y(k-1)+0.0644\,y(k-2)+0.0701\,y(k-3) \\ \qquad =-0.3621\,\Delta u_3(k-1) \end{cases}$$

The other general predictive controller C1 is designed as the same method.

V. SIMULATIONS

In a certain rare earth company, product yttrium should be extracted with the purity reached more than 0.99. Judged by the experiences, the component content at monitoring point should be up to 0.8, othersive, the outlet product can't meet the requirement. At some time, u_1 is 51.42 L, u_2 is 4.5 L, u_3 is 8.11 L and x_F is 0.481mol/L. The output y obtained by the multiple linear models established above is 0.65 and according to the clustering algorithm submodel 3 is used to test component content online at this time. So using the corresponded controller to adjust the flow rate of scrubbing solvent u_3, the component content at monitoring point is up to the objective value 0.8 fast.Finally, compared with PID algorithm and simulated with MATLAB, results are shown in Fig.6 and Fig.7, respectively.

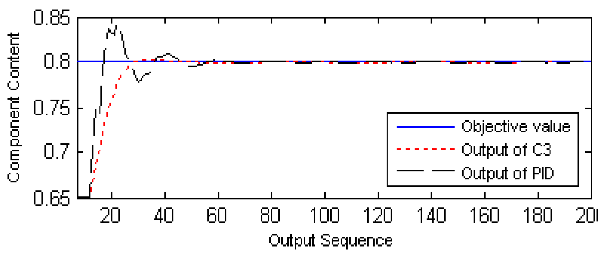

Fig.6 Comparison curves of tracking objective value

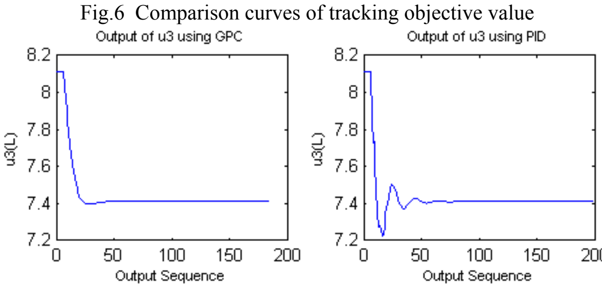

Fig.7 Varying curves of control variables as tuning u3

From Fig.6, compared with PID algorithm, it shows fast response speed and stability using GPC. And from Fig.7, the changes of u_3 using PID are unstable and oscillating, all of which are not suitable in practice.

VI. CONCLUSION

In this paper, considering the nonlinear dynamic model of rare earth extraction process, the multiple model modeling and control method is designed. Using the improved subtractive clustering algorithm, the extraction process is described by nonredundant multiple linear models with the same model structure and different parameters. Simultaneously, by using of switching index, the optimal model for measuring the component content online is constructed. Compared with the real industrial data, it shows that the modeling method has better generalization ability and higher prediction accuracy. Then, taking controlling the flow rare of scrubbing solvent as an example, GPC controller is designed in order to realize predictive control of component content in rare earth extraction process. Results show that the multiple model predictive control proposed is effective.

ACKNOWLEDGMENT

The authors acknowledged the National Natural Science Foundation of China(60864004, 51174091, 61164013) and the National 863 Plans Projects(2008AA04Z129) for having provided the financial support for this work.

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