Component Content Soft-sensor Based on Neural Networks in Rare-earth Countercurrent Extraction Process[1)]

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Abstract Throught fusion of the mechanism modeling and the neural networks modeling, a component content soft-sensor, which is composed of the equilibrium calculation model for multi-component rare earth extraction and the error compensation model of fuzzy system, is proposed to solve the problem that the component content in countercurrent rare-earth extraction process is hardly measured on-line. An industry experiment in the extraction Y process by HAB using this hybrid soft-sensor proves its effectiveness.

Key words Rare-earth, countercurrent extraction, soft-sensor, equilibrium calculation model, neural networks

1 Introduction

China has the most abundant rare-earth resource in the world[1,2]. But the extraction process automation is still in the stage that component content is measured off-line, and the process is controlled by experience and parameters are regulated by hands. This situation leads to low efficient production rate, high resource consumption and unstable production quality, and limits the rare-earth industry development[2]. To implement automation in the rare-earth extraction process, the on-line component content measuring must be achieved at first. Main component content measuring methods include the X-ray absorb spectrometer, X-ray energy spectrometer, Iso-topic X-fluorescence energy spectrometer, on-line spectrophotometers, *etc*[3,4]. These instruments have not been widely used in industry because of high cost, low reliability in continuous operation, complex maintenance, delay in measurement and low accuracy. The soft sensor method, on the other hand, provides a new way to on-line measure component content in the rare-earth countercurrent extraction process. We will further our research in [4] by fusion of the mechanism modeling and the intelligent modeling and propose a hybrid soft-sensor of the rare earth component content which contributes to better prediction accuracy and wider applicability. An industry experiment in the extraction Y process by HAB using this hybrid soft-sensor proves its effectiveness.

2 Description of rare-earth extraction process

A two component (A and B) countercurrent extraction process is shown in Fig. 1, where A is the easily extracted component and B is the hard extracted component. The left side is the extraction section composed of n stage mix-clarifiers. The right side is the scrub section composed of m stage mix-clarifiers. In Fig. 1, u_1 is the flow of rare earth feed, u_2 is the flow of extraction solvent, u_3 is the flow of scrub solvent, u_4 and u_5 are the distributions of A and B in the feed, respectively, where $u_4 + u_5 = 1$. ρ_A is the organic phase product purity of A at the exit and ρ_B is the aqueous phase product purity of B at the exit. $\rho_{A,k}$ is organic phase component content at the specified sampling point in scrub section and $\rho_{B,k}$ is aqueous phase component content at the specified sampling point in extraction section.

Since the whole process is composed of dozens of up to one hundred stages, the flow regulation of extraction solvent, scrub solvent and the feed can not influence the product purity at the exit until a long-time delay (often hours even days). For the above reason, the sampling point is set near the exit and the exit product purity (ρ_A, ρ_B) is guaranteed by measuring and control of the component contents ($\rho_{A,k}, \rho_{B,k}$) at the sampling point. According to countercurrent extraction principle, the parameters $\rho(\rho_{A,k}$ or $\rho_{B,k})$, u_1, u_2, u_3 and u_4 have the following nonlinear relationship

$$\rho = f\{u_1, u_2, u_3, u_4, \omega\} \tag{1}$$

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where $f\{\cdot\}$ is the complicated nonlinear function and ω is the disturbance. How to measure the parameters $\rho(\rho_{A,k}$ or $\rho_{B,k})$ has become the key point of rare-earth process automation.

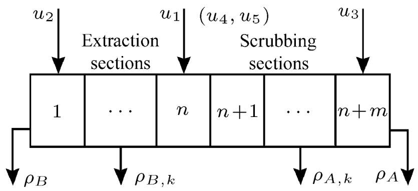

Fig. 1 Rare earth countercurrent extraction process

3 Method of component content soft-sensor in the rare earth extraction process

3.1 Strategy of component content soft-sensor in rare earth extraction process

Since the countercurrent rare-earth extraction process has nonlinear dynamics and uncertainty, it is difficult to model this process by simple methods including mechanism modeling or parameters estimation methods[5]. The framework of rare-earth extraction component content soft-sensor system is described in Fig. 2.

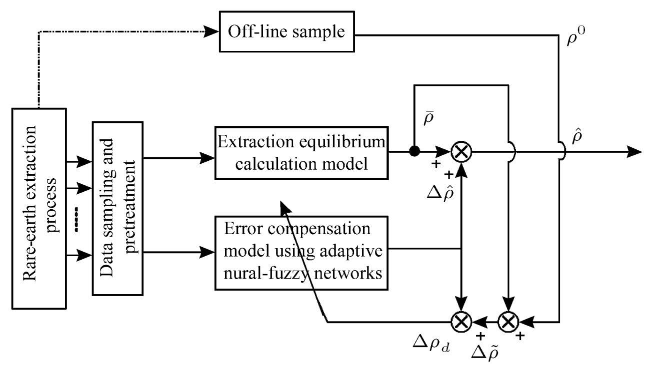

Fig. 2 Framework of rare-earth extraction component content soft-sensor

The whole system is composed of data sampling and pretreatment subsystem, extraction equilibrium calculation model and error compensation model using adaptive neural-fuzzy networks. Parameter ρ^0 is the component content assay value, parameter $\bar{\rho}$ is the output of countercurrent extraction equilibrium calculation model, $\Delta\tilde{\rho} = \rho^0 - \bar{\rho}$ is the modeling error, and parameter $\Delta\hat{\rho}$ is the output of component content error compensation model. $\Delta\rho_d = \Delta\tilde{\rho} - \Delta\hat{\rho}$ is used to train the modeling error compensation model. Then the soft-sensor output

$$\hat{\rho} = \bar{\rho} + \Delta\hat{\rho} \tag{2}$$

3.2 Equilibrium calculation model for multi-component countercurrent rare-earth extraction

For the rare-earth countercurrent extraction process shown in Fig. 1, when the component A and B reach the extraction balance at every stage, this state can be described by Fig. 3.

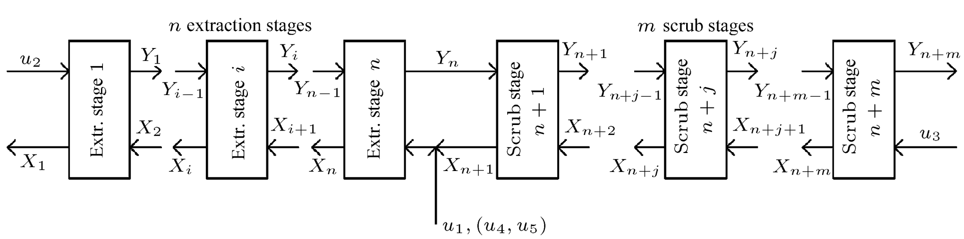

Fig. 3 Balance of rare-earth countercurrent extraction separation process

In Fig. 3 $\boldsymbol{X}_k = [x_{A,k}, x_{B,k}]^{\mathrm{T}}$, $\boldsymbol{Y}_k = [y_{A,k}, y_{B,k}]^{\mathrm{T}}$. $x_{A,k}, x_{B,k}, y_{A,k}$, and $y_{B,k}$ $(k = 1, 2, \cdots, n+m)$ are the corresponding quantities of A and B in the aqueous phase and organic phase at each stage.

The A component content $\rho_{A,k}$ in organic phase at the sampling point of scrub section and the B component content $\rho_{B,k}$ in aqueous phase at the sampling point of extraction section can be calculated by

$$\begin{cases} \bar{\rho}_{B,k} = x_{B,k}/(x_{A,k} + x_{B,k}) \times 100\%, & k = 1, 2, \cdots, n \\ \bar{\rho}_{A,k} = y_{A,k}/(y_{A,k} + y_{B,k}) \times 100\%, & k = n_1, \cdots, n+m \end{cases} \tag{3}$$

To get the values of $\bar{\rho}_{A,k}$ and $\bar{\rho}_{B,k}$, the parameters $x_{A,k}, x_{B,k}, y_{A,k}$, and $y_{B,k}$ $(k = 1, 2, \cdots, n+m)$ must be calculated at first.

According to the countercurrent extraction principle[1], after the first extraction equilibrium operation, the components A and B satisfied the following extraction equilibrium relationship:

$$\beta_k = y_{A,k}(t) \cdot x_{B,k}(t) / y_{B,k}(t) \cdot x_{A,k}(t), \ k = 1, 2, \cdots, n \tag{4}$$

$$y_{A,k}(t) + y_{B,k}(t) = S, \ k = 1, 2, \cdots, n \tag{5}$$

$$x_{A,k}(t) + y_{A,k}(t) = M_{A,k}(t), \ x_{B,k}(t) + y_{B,k}(t) = M_{B,k}(t), \ k = 1, 2, \cdots, n+m \tag{6}$$

$$\beta'_k = y_{A,k}(t) \cdot x_{B,k}(t) / y_{B,k}(t) \cdot x_{A,k}(t), \ k = n+1, \cdots, n+m \tag{7}$$

$$x_{A,k}(t) + x_{B,k}(t) = W, \ k = n+1, \cdots, n+m \tag{8}$$

where β_k and β'_k are extraction section average separation coefficient and scrub section average separation coefficient, respectively, S and W are corresponding organic extraction quantity and aqueous phase scrub quantity decided by countercurrent technics, when $u_1 = 1$, t denotes the times of extraction equilibrium operation. $M_{A,k}(t)$ and $M_{B,k}(t)$ are the total quantities of components A and B at each stage in the t-time extraction equilibrium operation and vary with the two-phase distribution data $x_{A,k}(t)$, $x_{B,k}(t)$, $y_{A,k}(t)$, and $y_{B,k}(t)$. At the initial time $(t = 1)$, they are decided by the fluid filling the tank. Solving (4)$\sim$(8) can get $x_{A,k}(t)$, $x_{B,k}(t)$, $y_{A,k}(t)$, and $y_{B,k}(t)$, $k = 1, 2, \cdots, n+m$.

According to the property of extraction process that organic phase and aqueous phase flow in the opposite directions, the two phases flowing into k stage are the organic phase in $k-1$ stage and the aqueous phase in $k+1$ stage, respectively. Hence, the quantity of components A and B at k stage in $t+1$ time extraction equilibrium operation is

$$\begin{cases} M_{A,k}(t+1) = x_{A,k+1}(t) + y_{A,k-1}(t) \\ M_{B,k}(t+1) = x_{B,k+1}(t) + y_{B,k-1}(t) \end{cases} \tag{9}$$

Fig. 4 is the flow chart to calculate $\bar{\rho}_{B,k}$ and $\bar{\rho}_{A,k}$ according to the equilibrium calculation model for countercurrent extraction.

Set $t = 1$; then use (4)$\sim$(9) to compute until $\begin{cases} |x_{A,k}(t) - x_{A,k}(t-1)| < \varepsilon_1 \\ |y_{A,k}(t) - y_{A,k}(t-1)| < \varepsilon_2 \end{cases}$, where ε_1 and ε_2 are specified small positive constants. At this moment, the whole countercurrent extraction process is considered to reach equilibrium and get the distribution data $x_{A,k}$, $x_{B,k}$, $y_{A,k}$, and $y_{B,k}$ of components A and B at every stage. Then using (3) one can get $\bar{\rho}_{A,k}$ and $\bar{\rho}_{B,k}$.

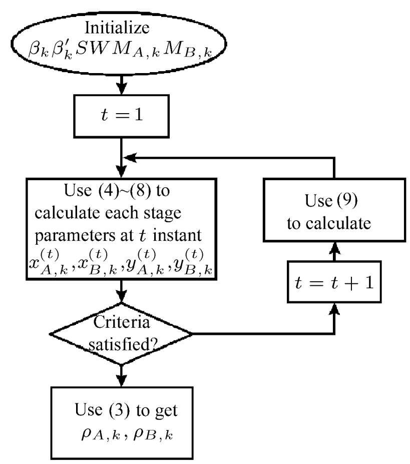

Fig. 4 Calculation flowchart using the equilibrium model

The equilibrium calculation model for countercurrent extraction process is obtained under the assumption that the mix extraction ratio is constant. Since there are many influencing factors, the real extraction production process is not always in the equilibrium state. The above conditions lead to obvious difference between the calculation result using this model and the real measuring result. If the error can be estimated and the estimated value can be used to compensate the output of equilibrium model, the accuracy of the rare earth extraction component content soft-sensor can be improved.

3.3 Component content error compensation model based on adaptive neural-fuzzy networks

Component content modeling error $\Delta\tilde{\rho}$ is influenced by the flow of rare earth feed and the extraction solvent, the PH value of scrub solvent and the variation of temperature. Using the adaptive neural-fuzzy networks[6~8] which is shown in Fig. 5 one can implement the component content error compensation model. The input are the flow of rare earth feed u_1, the flow of extraction solvent u_2, the flow of scrub solvent u_3, and the feed distribution u_4. The output of the error compensation model is $\Delta\hat{\rho}$.

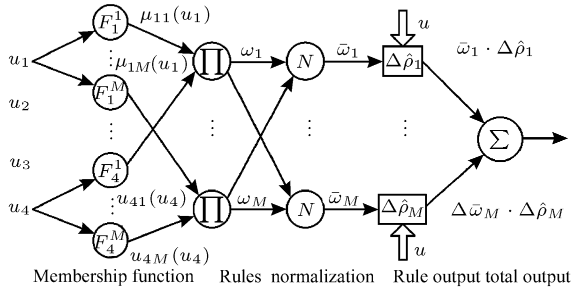

Fig. 5 Network structures of the adaptive neural-fuzzy networks

The number of rules is eight by using subtraction clustering[9] according to the sampled data. The whole error compensation model can be described by the following rules.

$$\begin{aligned} R^i:& \text{ if } (u_1 \text{ is } F_1^i) \text{ and } (u_2 \text{ is } F_2^i) \text{ and } (u_3 \text{ is } F_3^i) \text{ and } (u_4 \text{ is } F_4^i) \\ & \text{then } \Delta\hat{\rho}_i = p_0^i + p_1^i \cdot u_1 + p_2^i \cdot u_2 + p_3^i \cdot u_3 + p_4^i \cdot u_4,\ i = 1, 2, \cdots, 8 \end{aligned} \tag{10}$$

where R^i denotes the ith fuzzy rule, $p_k^i (i = 1, 2, \cdots, 8; k = 0, 1, 2, 3, 4)$ is called conclusion parameter, F_j^i denotes the ith fuzzy set of $u_j (j = 1, 2, 3, 4)$, the membership function $\mu_{ij}(u_j)$ is

$$\mu_{ij}(u_j) = \exp\left[-\frac{(u_j - m_{ij})^2}{2\sigma_{ij}^2}\right],\ i = 1, 2, \cdots, 8,\ j = 1, 2, 3, 4 \tag{11}$$

where m_{ij} and σ_{ij} are the center and the width of the membership function and $\{\sigma_{ij}, m_{ij} | i = 1, 2, \cdots, 8,\ j = 1, 2, 3, 4\}$ are called precondition parameters.

The output $\Delta\hat{\rho}$ is

$$\Delta\hat{\rho} = \sum_{i=1}^{8} \bar{\omega}_i \cdot \Delta\hat{\rho}_i \tag{12}$$

where

$$\bar{\omega}_i = \omega_i \Big/ \sum_{k=1}^{8} \omega_k,\ i = 1, 2, \cdots, 8 \tag{13}$$

$$\omega_i = \prod_{j=1}^{4} \mu_{ij}(u_j),\ i = 1, 2, \cdots, 8 \tag{14}$$

From (11)~(15),

$$\Delta\hat{\rho} = (\sum_{i=1}^{8} \Delta\rho_i \cdot \prod_{j=1}^{4} \mu_{ij}(u_j)) \Big/ (\sum_{i=1}^{8} \prod_{j=1}^{4} \mu_{ij}(u_j)) \tag{15}$$

where $\Delta\hat{\rho}$ can be replaced by estimation value $\Delta\tilde{\rho}$, conclusion parameters p_k^i can be obtained by using the least squares estimate algorithm to identify those parameters from (15).

The regulation algorithm of precondition parameters m_{ij} and σ_{ij} is

$$m_{ij}(k+1) = m_{ij} - \alpha_m \frac{\partial E}{\partial m_{ij}} = m_{ij}(k) - \alpha_m(\Delta\hat{\rho}(k) - \Delta\tilde{\rho}(k))(\Delta\hat{\rho}_i(k) -$$

$$\Delta\hat{\rho}(k))\frac{(u_j(k)-m_{ij}(k))}{\sigma_{ij}^2(k)}\phi_i(u),\ i=1,2,\cdots,8;\ j=1,2,3,4 \tag{16}$$

$$\sigma_{ij}(k+1)=\sigma_{ij}-\alpha_\sigma\frac{\partial E}{\partial\sigma_{ij}}=\sigma_{ij}(k)-\alpha_\sigma(\Delta\hat{\rho}(k)-\Delta\tilde{\rho}(k))(\Delta\hat{\rho}_i(k)-$$

$$\Delta\hat{\rho}(k))\frac{(u_j(k)-m_{ij}(k))^2}{\sigma_{ij}^3(k)}\phi_i(u),\ i=1,2,\cdots,8;\ j=1,2,3,4 \tag{17}$$

where $E=\frac{1}{2}\sum_{l=1}^{N}(\Delta\rho_d(l))^2$, $\phi_i(u)=(\prod_{j=1}^{4}\mu_{ij}(u_j))\Big/(\sum_{i=1}^{8}\prod_{j=1}^{4}\mu_{ij}(u_j))$, learning rate a_m and α_σ can be chosen by experiment.

3.4 Rare-earth extraction component content soft sensor algorithm

Introduce robust mean square error (RMSE) and max error (MAXE) as the component content soft sensor verification indexes.

$$RMSE=\sqrt{\frac{1}{N}\sum_{k=1}^{N}(\hat{\rho}_k-\rho_k^0)^2},\quad MAXE=\max_{k=1}^{N}(|\hat{\rho}_k-\rho_k^0|) \tag{18}$$

where $k=1,2,\cdots,N$ is the number of verification data, ρ_k^0 is the component content real measured value, $\hat{\rho}_k$ is the component content soft-sensor output, N is the number of the data.

According to the mechanism requirement of the rare earth extraction process, we choose $RMSE\leqslant 4$, and $MAXE\leqslant 10$. When the validation indexes (18) are not satisfied, it needs to rebuild the component content error compensation model. The whole soft-sensor algorithm is summarized as follows:

Step 1. Sample the flow data and the feed material distribution u_1,u_2,u_3,u_4, then decide parameter $\beta_k,\beta_k',S,W,M_{A,k},M_{B,k}$.

Step 2. Calculate the component content prediction value $\bar{\rho}$ at the measurement point using countercurrent extraction equilibrium model (4)∼(9) according to the procedure shown in Fig. 4.

Step 3. Use input $u_j(j=1,2,3,4)$ to calculate parameters. Calculate $\mu_{ij}(u_j)$ by (11), ω_i by (14), $\bar{\omega}_i$ by (13), $\Delta\rho_i$ by (10) and component content error compensation value $\Delta\hat{\rho}$ by (12).

Step 4. Use (2) to get the soft sensor output $\hat{\rho}$.

4 Industry experiment of soft-sensor in extraction Y process by HAB

A company uses extraction solvent HAB to extract high pure Y from the rare earth containing. The whole product lines are composed of three sections $Y_2O_3>40\%$. The object of the industry experiment of soft-sensor is the first section. This section includes 28 extraction stages and 32 scrub stages. The input of this section is the feed containing $Y_2O_3>40\%$, scrub solvent (3N HCL). The output of this section is Y_2O_3 with purity $>99\%$ and low Y mixed rare earth with $Y_2O_3<0.5\%$ at each exit respectively. To guarantee the product purity requirement at each exit, the sampling point is set at some stage according to extraction product technic process automation requirement.

100 group data sampled from the extraction are used to construct the modeling data set. Part of this set are shown in Table 1, where u_1 is the feed flow, u_2 is extraction solvent flow, u_3 is scrub solvent flow, u_4 is the content of Y in the feed and ρ_l^0 is the real measured component content data. These 100 group sampling data are used to calculate Y component content $\bar{\rho}(l)$ at the measured spot by (4)∼(9) and Fig. 4. The result is shown in Table 1.

Table 1 Modeling sample data of extraction Y by HAB

Group	u_1	u_2	u_3	u_4	$\rho^0(l)$	$\bar{\rho}(l)$
1	3.01	31.48	4.65	0.546	88.54	93.91
2	3.04	32.15	4.79	0.546	86.34	94.83
3	5.01	57.24	8.71	0.546	89.51	96.39
4	6.05	63.22	9.36	0.546	87.63	94.11
⋮	⋮	⋮	⋮	⋮	⋮	⋮
99	4.51	45.91	7.32	0.413	43.61	47.33
100	5.4	55.34	8.83	0.413	42.69	47.22

Construct the error compensation model sample data set $\Delta\tilde{\rho}(l) = \rho^0(l) - \bar{\rho}(l)$ and use the least square algorithm to get the conclusion parameters p_k^i. The precondition parameters are adjusted by (16), (17). The result is shown in Table 2.

Table 2 Parameters of the error compensation model

Rules	Precondition parameters								Conclusion parameters				
	F_1^i		F_2^i		F_3^i		F_4^i						
	m_{i1}	σ_{i1}	m_{i2}	σ_{i2}	m_{i3}	σ_{i4}	m_{i4}	σ_{i4}	p_0^i	p_1^i	p_2^i	p_3^i	p_4^i
1	3.04	1.031	30.38	12.78	4.65	2.01	0.476	0.0301	19.15	-5.087	18.07	-69.59	42.70
2	6.03	1.031	64.40	12.78	9.63	2.01	0.547	0.0200	26.33	-6.282	28.48	37.61	-51.48
3	2.02	1.031	20.28	12.78	3.05	2.01	0.503	0.0048	-435.3	179.3	-912.3	7401	-3746
4	5.05	1.031	48.85	12.78	7.39	2.01	0.472	0.0243	-15.45	8.497	-42.99	-150.1	49.58
5	2.51	1.031	25.21	12.78	4.01	2.01	0.414	0.0293	8.540	-8.297	44.36	-225.7	96.82
6	6.84	1.031	68.74	12.78	10.3	2.01	0.503	0.0196	126.2	-48.96	247.5	1540	-844.7
7	2.02	1.031	21.35	12.78	3.24	2.01	0.517	0.0339	-32.15	19.73	-110.0	-237.3	112.0
8	4.52	1.031	52.02	12.78	8.54	2.01	0.414	0.0301	8.362	-4.66	24.63	-175.5	64.69

50 group data sampled in extraction process are shown in Table 3. These data are used to predict the component content in the measurement spot. $\bar{\rho}$ is the output of Y component content, extraction equilibrium calculation model can be obtained by (4)$\sim$(9) and the Fig. 4. $\Delta\hat{\rho}$ is the output of the error compensation model. $\hat{\rho}$ is the output of the soft-sensor, *i.e.* the output of the hybrid model including the equilibrium calculation model and the error compensation model. They are shown in Table 3.

Table 3 Part component content prediction values of extraction Y process by HAB

Group	u_1	u_2	u_3	u_4	ρ^0	$\bar{\rho}$	$\Delta\hat{\rho}$	$\bar{\rho}$
1	5.4	55.47	8.49	0.481	63.61	75.01	-6.901	68.109
2	5.3	59.77	9.49	0.481	67.8	77.84	-8.246	69.594
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
13	4.01	45.76	7.01	0.535	82.4	94.98	-10.21	84.765
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	2.5	29.58	4.57	0.535	83.5	95.47	-11.65	83.82
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
30	3.51	41.17	6.38	0.529	82.8	94.43	-10.67	83.755
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
49	5.51	61.79	9.94	0.439	52.1	55.42	-7.7	47.72
50	4.53	43.67	6.75	0.439	51.2	56.73	-5.76	50.97

The Y content curves of the real measured data, the output data of countercurrent extraction equilibrium calculation model (mechanics model) and the soft-sensor output data at the sampling point are shown in Fig. 6. From Fig. 6, it is shown that the varied trends of the equilibrium model output and the soft-sensor output are identical with the real sampling data. At the points 13, 19 and 30 in Fig. 6, the errors between the output of the equilibrium calculation model and the real sampling data are 12.58, 11.99 and 11.63, respectively, but the errors between the soft-sensor output and the real sampling data are 2.365, -0.320 and 0.955. RMSE and MAXE for the equilibrium calculation model are RMSE=2.918 and MAXE=12.58. In order to control the rare earth extraction process, it is required that MAXE<10. For the soft-sensor, RMSE=2.315 and MAXE=4.509. The proposed method has been successfully applied to the rare-earth countercurrent extraction process[10].

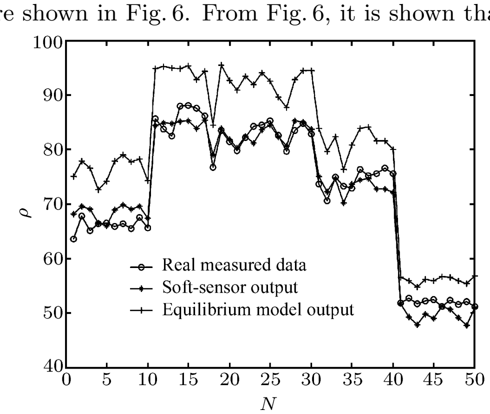

Fig. 6 Y content curves at sampling stage

5 Conclusions

The component content soft-sensor model of the rare-earth countercurrent extraction process proposed in this paper is a hybrid model composed of the countercurrent extraction equilibrium calculation model and the error compensation model using adaptive neural-fuzzy networks. The proposed hybrid model can be used in the case that dynamic disturbance exists. When dynamic disturbance exists, the original equilibrium calculation model has larger errors. The successful application of the soft-sensor model in the extraction Y product line by HAB shows that the proposed soft-sensor method is effective to solve the component content online measurement problem.

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