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Intelligent modeling and optimization on time-sharing power dispatching system for electrolytic zinc process①

WANG Ya-lin(王雅琳), GUI Wei-hua(桂卫华),
YANG Chun-hua(阳春华), HUANG Tai-song(黄泰松)
(College of Information Science and Engineering, Central South University of Technology,
Changsha 410083, P.R.China)

[Abstract] Based on real-time price counting of electric power, an optimization model of time-sharing power for electrolytic zinc process(EZP) was established by means of an incremental fuzzy neural network(FNN), which is adopted to approximate the relationship of current efficiency, current density and acidity. Penalty function introduced and optimal objective function reconstructed, a single-loop simulated annealing algorithm(SAA) by using mutation and extending searching spaces was used to obtain optimal time-sharing power scheme. Industrial practical results show that the whole system can greatly decrease the power consumption of EZP and increase the time-sharing profits.

[Key words] fuzzy neural network; optimization model of time-sharing power; simulated annealing algorithm
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1 INTRODUCTION

In metallurgical industry, electrolytic zinc process(EZP) is a great power-consuming process whose power consumption accounts for 80% of total power consumption of hydro-metallurgical process[1]. According to real-time price counting policy, power costs of EZP will be decreased obviously in the event of electrolysis with low current density in the period of high price and with high current density in the period of low price. However, if the current density is too high or too low, it will lead to high power consumption or low current efficiency. So it is imperative to seek optimal time-sharing power scheme that real-time price counting and state of zinc electrolysis are taken into account.

With the relatively constant temperature in EZP, current efficiency is mainly related to current density and acidity and their relationship is nonlinear. Fuzzy neural network (FNN)[2,3], which integrates the learning ability of neural networks and the human-like reasoning ability of the fuzzy logic systems into one framework[4], can arbitrarily approximate the nonlinear relationship through training multi-input/multi-output process data. So FNN is adopted to approximate their relationship. Simulated annealing[5], a random searching optimization technique which is based on the physical annealing of solids and derives from the Metropolis algorithm[6], only needs compute objective function in the process of iterating, and overcomes the shortage of conventional optimization methods which need differentiate objective function, so it can be used to optimize such intelligent model as FNN. In this paper, an single-loop SAA by using mutation and extending searching spaces is applied to optimal dispatching system of time-sharing power for EZP with FNN model. Industrial practical results suggest that the optimal time-sharing power scheme brought out large economic profits for EZP.

2 FUZZY NEURAL NETWORK MODEL

2.1 Architecture of FNN

A multi-input-multi-output system can always be separated into a group of multi-input-single-output systems, so a FNN with m inputs $\{x_1, x_2, \cdots, x_m\}$ and one output y is discussed and its network architecture is shown in Fig.1. The node functions in every layer are described as follows.

1) Layer 1

The node function in this layer is the membership function of the linguistic label A_{ij} and it specifies the degree to which the given input x_i satisfies the quantified A_{ij}. Using the Gaussian membership function, the node function can be expressed as

$$O^1_{ij} = \mu_{A_{ij}}(x_i) = \exp[-(\frac{x_i - c_{ij}}{\sigma_{ij}})^2] \qquad (1)$$

where c_{ij} and σ_{ij} are the center and width of the membership function of A_{ij}. The parameter sets $\{c_{ij}, \sigma_{ij}\}$ are referred to as antecedent parameters.

2) Layer 2

Every node in the layer is multiplier of the incoming signals whose output represents the firing strength of a rule. So the node function can be written as

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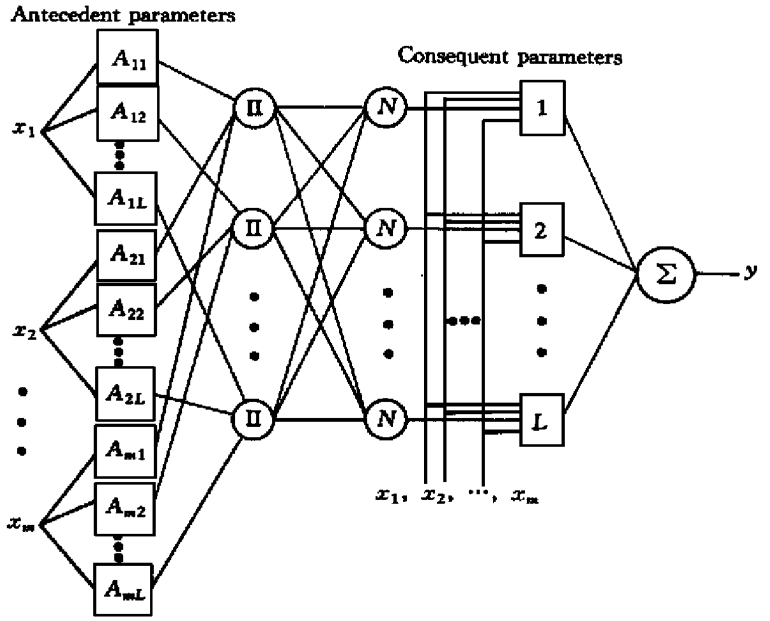

Fig.1 Network architecture of FNN

$$\omega_j = \prod_{i=1}^{m} \mu_{A_{ij}}(x_i) = \exp\left[-\sum_{i=1}^{m}\left(\frac{x_i - c_{ij}}{\sigma_{ij}}\right)^2\right] \quad (2)$$

3) Layer 3

The jth node in the layer calculates the ratio of the jth rule's firing strength to the sum of all rules' firing strengths:

$$\overline{\omega}_j = \omega_j / \sum_j \omega_j \quad (3)$$

4) Layer 4

Suppose the rule of FNN belongs to Takagi and Sugeno's type[7], the node membership in the layer can be expressed as

$$O_j^4 = \overline{\omega}_j f_j = \overline{\omega}_j(a_{0j} + a_{1j}x_1 + a_{2j}x_2 + \cdots + a_{mj}x_m) \quad (4)$$

where $\overline{\omega}_j$ is the output of layer 3, and the parameter sets $\{a_{0j}, a_{1j}, a_{2j}, \cdots, a_{mj}\}$ referred to as consequent parameters are decided in the process of training.

5) Layer 5

The node in the layer computes the overall output as the summation of all incoming signals, i.e.

$$O^5 = y = \sum_j \overline{\omega}_j f_j = \sum_j \omega_j f_j / \sum_j \omega_j \quad (5)$$

As mentioned above, FNN has the same architecture as neural network(NN), so it can be trained and learned as NN. On the other hand, FNN can reason as Fuzzy Logic(FL) because its nodes have definite physical meaning.

2.2 Incremental hybrid learning algorithm

Hybrid learning algorithm[8] is a combination of the gradient descent method and the least squares estimate(LSE). Each epoch of the hybrid learning procedure is composed of a forward pass and a backward pass. In the forward pass, antecedent parameters are fixed at first and LSE is adopted to calculate consequent parameters. On the contrary, in the backward pass, consequent parameters are fixed and gradient descent algorithm is used to update antecedent parameters. For most industrial processes, the plant is always varying with time, so incremental hybrid learning algorithm(IHLA) is proposed to on-line update these parameters. The following is the summary for the IHLA.

For each input/output data pair $\{x_{n1}, x_{n2}, \cdots, x_{nm}, y_n\}$, $\overline{\omega}_{nj}$ is calculated through Eqn.(1) to Eqn.(3) at first. Defined

$$\phi_n = [\overline{\omega}_{n1}, \overline{\omega}_{n1}x_{n1}, \overline{\omega}_{n1}x_{n2}, \cdots, \overline{\omega}_{n1}x_{nm}, \cdots, \overline{\omega}_{nL}, \overline{\omega}_{nL}x_{n1}, \overline{\omega}_{nL}x_{n2}, \cdots, \overline{\omega}_{nL}x_{nm}]^{\mathrm{T}},$$

$$\theta_n = [a_{01}, a_{11}, a_{21}, \cdots, a_{m1}, a_{02}, a_{12}, a_{22}, \cdots, a_{m2}, a_{0L}, a_{1L}, a_{2L}, \cdots, a_{mL}]^{\mathrm{T}}$$

where L is the number of fuzzy rule, Eqn.(5) is rewritten as

$$\hat{y}_n = \sum_{j=1}^{L} \overline{\omega}_{nj} f_j = \phi_n^{\mathrm{T}} \theta_n \quad (6)$$

so consequent parameters θ_n can be real-time updated according to

$$\left.\begin{aligned} \theta_n &= \theta_{n-1} + S_n\phi_n(y_n - \phi_n^{\mathrm{T}}\theta_{n-1}), \\ S_n &= \frac{1}{\lambda}\left[S_{n-1} - \frac{S_{n-1}\phi_n\phi_n^{\mathrm{T}}S_{n-1}}{\lambda + \phi_n^{\mathrm{T}}S_{n-1}\phi_n}\right] \end{aligned}\right\} \quad (7)$$

where S_n is often called covariance matrix, its initial value $S_0 = \rho\boldsymbol{I}$, where ρ is a positive large number and $\boldsymbol{I}$ is the identity matrix of dimension of $(m+1)L \times (m+1)L$, λ is the forgetting factor whose value is between 0 and 1. Based on the error function

$$E = \frac{1}{2}(y_n - \hat{y}_n)^2 \tag{8}$$

where $\hat{y}_n$ is gained through substituting the value of θ_n to Eqn.(6), antecedent parameters $\{c_{nij}, \sigma_{nij}\}$ are back-propagating updated by

$$\left.\begin{aligned} c_{nij} &= c_{(n-1)ij} + 2\eta\bar{\omega}_{nj}(y_n - \hat{y}_n)\cdot \\ &\quad (f_j - \hat{y}_n)(x_{ni} - c_{(n-1)ij})/\sigma^2_{(n-1)ij}, \\ \sigma_{ij} &= \sigma_{(n-1)ij} + 2\eta\bar{\omega}_{nj}(y_n - \hat{y}_n)\cdot \\ &\quad (f_j - \hat{y}_n)(x_{ni} - c_{(n-1)ij})^2/\sigma^3_{(n-1)ij} \end{aligned}\right\} \tag{9}$$

where η is learning rate. In the learning procedure, η is updated according to the following two heuristic rule[8]:

1) If the error measure undergoes four consecutive reductions, η is increased by 10%;

2) If the error measure undergoes two consecutive combinations of one increase and one reduction, η is decreased by 10%.

The number of membership functions in the IHLA is determined by the subtractive clustering method[9].

2.3 Simulation

Process data of EZP in a smelting works suggest that the relationship among current efficiency, current density and acidity is nonlinear. So IHLA is applied to approximate their relation, where current density and acidity are taken as the model input variables and current efficiency as the output variable. Approximating results is shown in Fig.2.

In Fig.2(a), the dots present the desired output and accordingly the solid line presents the model output gained by the way of FNN. In Fig.2(b), the maximal FNN error is less than 2% and the root mean square error of all data is only 0.3%. So it can be concluded that FNN model of current efficiency has good fitting precision.

3 OPTIMIZATION MODEL

At present, power price counting policy in Hunan province is based on 4 periods. In different periods, the prices of electric power are quite different. In order to keep the daily direct-current power cost be the lowest on condition that the quality and quantity of zinc meet requirements of production, the optimal current densities in four different periods are sought by an optimal dispatching system(ODS). The objective function of the optimization model can be expressed as follows:

$$Q = \sum_{i=1}^{4} p_i h_i \tag{10}$$

that is, minimize

$$Q = \sum_{i=1}^{4}(p_i V_i J_i S t_i n_b) \tag{11}$$

where p_i is the time-sharing power price, yuan/kWh; h_i is the power consumption in the ith period, kWh; V_i is the bath voltage, V; J_i is current density, A/m^2; $S = n_p \times S_0$ is the area that current passes, m^2; S_0 is area of a negative plate, m^2; and n_p is the negative plate number of a bath; n_b is the number of bath; t_i is the time of the ith period, h.

According to the practical production situation of a smelting works in Hunan province, the relationship between bath voltage and current density is shown as following,

$$V_i = a_0 + a_1 J_i \tag{12}$$

where a_0, a_1 are polynomial coefficients.

To ensure the quality and quantity of products, objective function should be subject to the following constraints.

1) Constraint of daily output

$$G = \sum_{i=1}^{4} G_i = \sum_{i=1}^{4} q J_i S t_i n_b \eta_i = C \tag{13}$$

where q is electrochemical equivalent of zinc, $q = 1.2202$ g/(A·h); C is the desired daily output of zinc, t. The current efficiency is related to the acidity of electrolyte and the current density J_i. Their relationship can be obtained by virtue of FNN above. The formula can be expressed as

$$\eta_i = \mathrm{fnn}(J_i, r_e) \tag{14}$$

where r_e is the acidity of electrolyte.

2) Constraint of the product quality and technological conditions

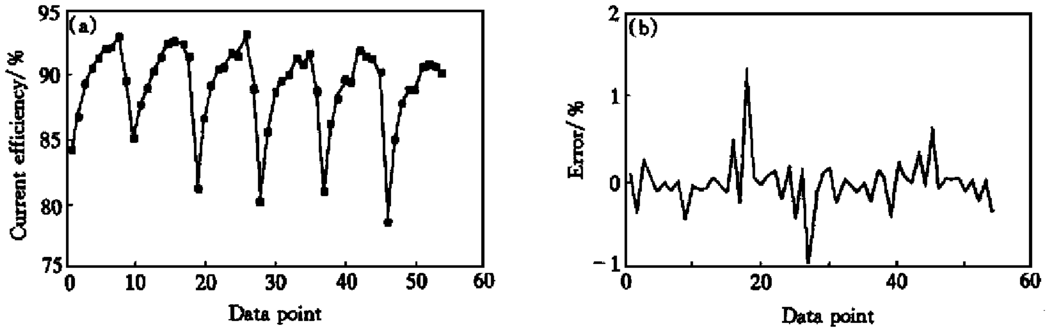

Fig.2 Approximating results of comparative curve of model output with desired output (a) and error curve of desired output and model output (b)

$$J_{\min} \leqslant J_i \leqslant J_{\max} \tag{15}$$

where $J_{\min}$ is the allowed minimum current density of EZP to avoid dissolving zinc cathodes at too low current density; $J_{\max}$ is the allowed maximum current density of EZP, which depends on capacity of cooling tower and maximum of power, etc.

So, the optimization model of time-sharing power system for EZP can be simplified as follows

$$\min Q = \min \sum_{i=1}^{4}(l_i V_i J_i), \quad s.t.\left\{\begin{array}{l} V_i = a_0 + a_1 J_i, \\ \eta_i = \mathrm{fnn}(J_i, r_e), \\ \sum_{i=1}^{4} b_i J_i \eta_i = C, \\ J_{\min} \leqslant J_i \leqslant J_{\max} \end{array}\right. \tag{16}$$

where $l_i = P_i S t_i n_b$; $b_i = q t_i S n_b$; $i = 1, 2, 3, 4$.

4 SIMULATED ANNEALING ALGORITHM

The convergent rate of SAA is mainly improved by virtue of constructing a new refresh function of annealing temperature (RFAT) such as the RFAT of an SAA[10] that the annealing temperature is inversely proportional to mth power of annealing time. But because the algorithm can't give a good solution to the situation that the search procedure is probably long-time trapped in a local point and unable to jump out, the reliability and satisfactory computational efficiency of finding global solution can't be ensured. So a single-loop SAA by using mutation and extending searching spaces is presented to solve the problem. The following is the summary for the proposed SAA which is going to be introduced in another paper in detail.

As for the global optimization problem as $\min_{x \in R^n} f(x)$, the proposed SAA is realized on the following steps:

1) Step 1

Give the initial solution $x^0 \in R^n$ and initial annealing temperature T_0, define maximum iterative times $k_{\max}$, time mutational proportion P_m as well as the later improved parameters k_b and α, calculate $f(x^0)$ and let $X^0 = x^0$, $X_{\min} = x^0$, $f_{\min} = f(x^0)$, $k = 0$;

2) Step 2

According to the given probability function

$$P(\boldsymbol{Z}^k | T_k) = \prod_{i=1}^{n} \frac{T_k^{1/m}}{2m(|Z_i^k| + T_k)^{(m+1)/m}} \tag{17}$$

where $\boldsymbol{Z}^k$ is the generated kth random vector, $\boldsymbol{Z}^k = (Z_1^k, Z_2^k, \cdots, Z_n^k)$, and T_k is the kth annealing temperature, $T_k > 0$.

Random vector $\boldsymbol{Z}^k$ is generated according to

$$Z_i^k = \mathrm{sign}(u_i)\, T_k\left(\frac{1}{|u_i|^m} - 1\right), \quad i = 1, 2, \cdots, n \tag{18}$$

where $u_1, u_2, \cdots, u_n$ is a group of pairwise independent random vectors uniformly distributed in $[-1, 1]$, $\mathrm{sign}(\cdot)$ is signum function, T_k is present annealing temperature and m is a given constant, $m \geqslant 1$.

Generate a new heuristic point $\boldsymbol{Y}^k = \boldsymbol{X}^k + \boldsymbol{Z}^k$ by using present iterative point $\boldsymbol{X}^k$ and random vector $\boldsymbol{Z}^k$ and calculate $f(\boldsymbol{Y}^k)$;

3) Step 3

Generate a random number δ uniformly distributed in $[0, 1]$, and calculate the probability $P_a(\boldsymbol{Y}^k | \boldsymbol{X}^k, T_k)$ of accepting $\boldsymbol{Y}^k$ at the present given iterative point $\boldsymbol{X}^k$ and temperature T_k, i.e.

$$P_a(\boldsymbol{Y}^k | \boldsymbol{X}^k, T_k) = \min\{1, \exp(\frac{f(\boldsymbol{X}^k) - f(\boldsymbol{Y}^k)}{T_k})\}.$$

If $\delta \leqslant P_a(\boldsymbol{Y}^k | \boldsymbol{X}^k, T_k)$, then $\boldsymbol{X}^{k+1} = \boldsymbol{Y}^k$, or else $\boldsymbol{X}^{k+1} = \boldsymbol{X}^k$. If the time that the value $\boldsymbol{X}^{k+1}$ keeps unchanged continuously exceeds $k_{\max} P_m$, then $\boldsymbol{X}^{k+1} = \boldsymbol{Y}^k$;

4) Step 4

Calculate iterative times k, if k is the multiple of k_b, then reassign initial annealing temperature T_0 according to

$$T_0^* = \alpha T_0 \tag{19}$$

5) Step 5

If $f(\boldsymbol{X}^{k+1}) < f_{\min}$, then $X_{\min} = \boldsymbol{X}^{k+1}$, $f_{\min} = f(\boldsymbol{X}^{k+1})$. If iterative terminal conditions are satisfied, then stop searching procedure and take $X_{\min}$ as global optimal solution, else generate a new temperature T_{k+1} according to given RFAT

$$T_{k+1} = T_0 / k^m, \quad k = 1, 2, \cdots \tag{20}$$

where T_0 is initial annealing temperature, k is annealing iterative times and m is the same as Eqn. (18).

let $k = k + 1$, and go to Step 2.

Considering that optimization model of time-sharing power for EZP comprises equation constraint and inequality constraint, it must be transformed in term of the following methods at first.

1) Penalty function introduced and the equation constraint substituted into objective function of the optimization model, the objection function is rewritten as

$$\hat{Q} = \sum_{i=1}^{4} l_i V_i J_i + M[C - \sum_{i=1}^{4} b_i J_i \mathrm{fnn}(J_i, r_e)] \tag{21}$$

where M is a penalty factor and its value is a positive large number.

2) The new heuristic point $\boldsymbol{Y}^k$ generated in Step

2 is forced to satisfy the inequality constraint according to the formula

$$Y_i^k = \begin{cases} J_{max} - (Y_i^k - J_{max}) \bmod (J_{max} - J_{min}), \\ Y_i^k > J_{max}; \\ Y_i^k, \\ J_{min} \leqslant Y_i^k \leqslant J_{max}; \\ J_{min} + (J_{min} - Y_i^k) \operatorname{mon}(J_{max} - J_{min}), \\ Y_i^k < J_{min} \end{cases} \quad (22)$$

After pretreatment, the proposed SAA can be used to optimize the ODS.

5 INDUSTRIAL APPLICATION

The applicable software of ODS was written with Visual Basic 5.0. FNN model between current efficiency and current density on different acidities is identified and modified on-line. Many functions such as computation of material balance, optimal calculation, comparison of optimization efficiency, synthetic data processing and so on were realized. The ODS of time-sharing power for EZP with FNN model and SAA optimization method has been running in a smelting works since April, 1999. The practical results in a week after the system was applied are shown in Table 1.

Table 1 Practical results

Date	Expected output /t	Practical output /t	Current density /(A·m^{-2}) J_1	J_2	J_3	J_4	Power consumption /(kWh·t^{-1})	Time-sharing profits /yuan
May 3, 1999	480 280	478.5 280.6	200 200	457 357	590 596	590 598	3 027 3 046	141 143
May 4, 1999	480 280	481.1 279.5	200 200	457 357	563 596	590 598	3 006 3 030	183 978
May 5, 1999	480 280	480.0 281.1	200 200	457 357	563 596	590 598	3 032 3 049	140 084
May 6, 1999	480 280	480.2 280.1	200 200	457 357	586 601	590 601	2 990 3 022	202 066
May 7, 1999	490 280	491.1 279.6	200 200	483 357	563 598	590 601	3 014 3 043	143 035

Table 1 shows that average direct-current power consumption per ton zinc is 3 030.5 kWh/t and time-sharing profits per month is up to 3 464 000 yuan. Compared with 3 052.2 kWh/t and 2 777 000 yuan before, it can be concluded that the electrolysis process of zinc runs regularly, power consumption decreases and time-sharing profits are notable after the optimal time-sharing power scheme is applied to arrangement of production.

6 CONCLUSIONS

According to real-time price counting policy of electric power, the time-sharing power optimization model for EZP is established. And the single-loop SAA by using mutation and extending searching spaces is used to optimize the intelligent model with FNN. The time-sharing power optimal dispatch system has been applied to a smelting works. The results show that the system can greatly decrease the power consumption per ton zinc and increase the time-sharing profits. So how to apply computer techniques and advanced control technologies to industrial process to raise enterprises' economic profits is an important project worthy of further research.

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