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Full Length Research Paper

A novel soft sensor model based on artificial neural network in the fermentation process

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Some crucial process variables in fermentation process could not be measured directly. Soft sensor technology provided an effective way to solve the problem. There has been considerable interest in modeling a soft sensor by using artificial neural network (ANN) in bioprocess. To generate a more efficient soft sensor model, we proposed a novel soft sensor model based on artificial neural network (SS-ANN). By analyzing a grey-box model of fermentation process, the secondary variables were selected. In modeling, on-line measurable variables could be taken as the input of ANN and the output is the derivatives of immeasurable variables. The estimated values of immeasurable variables were calculated by integrating the outputs of the well-trained ANN. The novel SS-ANN is different from the general SS-ANN. Experimental results of erythromycin fermentation process showed the novel soft sensor model could estimate mycelia concentration, sugar concentration and chemical potency with higher accuracy and generalization ability than the general soft sensor based on ANN. The novel soft sensor modeling method provides the theory basis for selecting the secondary variables. The dynamic characteristic of the process is considered, the novel model improves the estimation accuracy and generation ability. It can be concluded that the soft sensor model mentioned in this paper is reasonable and effective.

Key words: Soft sensor model, artificial neural network, fermentation process, dynamic characteristics.

INTRODUCTION

It is well known that the precise and real-time measurement of some crucial variables in biochemical process industries is essential to raise the productivity and quality of the products as well as safeguard the facilities. Existing sensor technology does not allow the most significant indicators of bioprocess behavior to be measured accurately and reliably on-line. Instead, these measurements are performed off-line in the laboratory, providing delayed and relatively infrequent information. It is very difficult to recognize early signs of an undesirable fermentation, hindering on-line control actions and ultimately leading to a significant waste of time and resource. This problem has led to the development of soft sensors (Gee et al., 1996; Cheruy, 1997; Assis and Filho, 2000) whose secondary variables are directly on-line measurable variables while whose key variables would be the variables to be estimated. These soft sensor models utilize mathematical models (ranging from structured to data-based) and algorithms, together with available online information such as temperature, PH value, dissolved oxygen tension, relative pressure and agitator-rotated speed in fermentation, to estimate the crucial bioprocess parameters.

Most of soft sensor modeling methods can be summarized into two different classes, namely model-driven and data-driven (Petr et al., 2009; Vapnik, 1995). Mode-driven methods usually cause severe errors of the on-line estimations because suffering from the inaccuracies of available instruments and depending on the accuracy of the process model (Kesavan et al., 2000; Gulnur and Cenk, 2002). The data-driven soft sensors gained increasing popularity in the process industry. Because

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Abbreviations: ANN, Artificial neural network; **SS-ANN,** soft sensor model based on artificial neural network.

these data-driven models are based on the data measured within the processing plants, and thus describe the real process conditions. As a data-driven modeling method, ANN pos-sesses the ability to approximate any complex nonlinear relationships to any desired degree of accuracy with less a prior knowledge. There has been considerable interest and rapid development in soft sensor modeling based on ANN in process industry (Bo et al., 2003; Susan et al., 1997). But it is still very difficult to obtain satisfying soft sensor model in the absence of construction theory. It is important to establish a strict construction theory of SS-ANN and improve its performance for the on-line esti-mation of the key immeasurable variables in biochemical process.

Motivated by this, a novel soft sensor model based on ANN is proposed and used to estimate mycelia concen-tration, sugar concentration and chemical potency in erythromycin fermentation process which can hardly be measured by actual chemical or physical sensor. The measurable variables are taken as the ANN input and the ANN output is the derivatives of immeasurable variables. The estimated values of immeasurable variables are obtained by integrating the output of well-trained ANN. The accuracy of estimation and generalization ability was improved.

NOVEL SOFT SENSOR MODELING METHOD

Problem description

Consider the following nonlinear model described using m first-order differential equations

$$\frac{dx_i}{dt} = f_i(x_1, \cdots, x_m) \quad i = 1, \cdots, L \tag{1}$$

Where, x_i is the state variables; $f_i(x)$ is a real-valued continuous function with uncertainty of m variables. $(x_1, \cdots, x_L)$ is the immeasurable variable and $(x_{L+1}, \cdots, x_m)$ is the measurable variable.

Assumption: There exist function relations between measurable variables and immeasurable variables as follow.

$$x_i = g_i(t, x_{L+1}, \cdots, x_m) \tag{2}$$

The time derivative of x_i can be written as

$$\frac{dx_i}{dt} = \varphi_i(t, x_{L+1}, \cdots, x_m) \tag{3}$$

Immeasurable variables can be obtained as following

$$x_i = \int \varphi_i(t, x_{L+1}, \cdots, x_m) dt \tag{4}$$

Where, $g_i(\cdot)$, $\varphi_i(\cdot)$ $i = 1, \cdots, L$ is the real-valued continuous function with uncertainty.

Remark: The assumption as above mentioned is very important for selecting the secondary variables of soft sensor model. It illustrates that there exists uncertain relation between the immeasurable variables and the measurable ones.

Novel soft sensor model based on ANN

In this paper, a three-layered feed-forward ANN, including m-L+1 real-valued inputs, one hidden layer with H neurons and one output layer with L real-valued outputs, is used to approximate the nonlinear function $\varphi_i(\cdot)$. For a given set of input values $(t, x_{L+1}, \cdots, x_m)^T$, the kth output of the network is described in the following form

$$N_k(t, x_{L+1}, \cdots, x_m, P) = \sum_{i=1}^{H} v_{ki} s[w_i t + (\sum_{j=L+1}^{m} w_{ij} y_j) + b_i] \\ k = 1, 2, \cdots, L \tag{5}$$

Where, v_{ki} is the synaptic weight from the ith hidden neuron to the output; w_i is the synaptic coefficient from the time input to the ith hidden neuron; w_{ij} is the synaptic coefficient from the jth component of the spatial inputs to the ith hidden neuron; b_i is the bias value of the ith hidden neuron and $s: \mathbb{R} \to \mathbb{R}$ is the logistic activation function.

Denote $P = (v_{ki}, w_i, w_{ij}, b_i)$ as adjustable parameter set.

In training, the desired value of ANN is $(\dot{x}_1, \cdots, \dot{x}_L)$ and the parameter set is adjusted by Levenberg Marquardt algorithm which is used to optimize BP ANN. The corresponding total error function will be

$$E(P) = \sum_{i=1}^{L} \left\{ \sum_{l=1}^{n} \left| \dot{x}_i^l - N_i(t_l, x_{L+1}^l, \cdots, x_m^l, P_i) \right|^p \right\}^{\frac{1}{p}} \tag{6}$$

Where, p is a positive constant; $\{t^l, x_{L+1}^l, \cdots, x_m^l\}_{l=1}^n$ is the sample data collected; $\{\dot{x}_1^l, \dot{x}_2^l \cdots, \dot{x}_L^l\}_{l=1}^n$ is the first-order derivative of $\{x^l{}_1, x^l{}_2 \cdots, x_L^l\}_{l=1}^n$ and obtained by using 5-point numerical derivative method and n is the number of

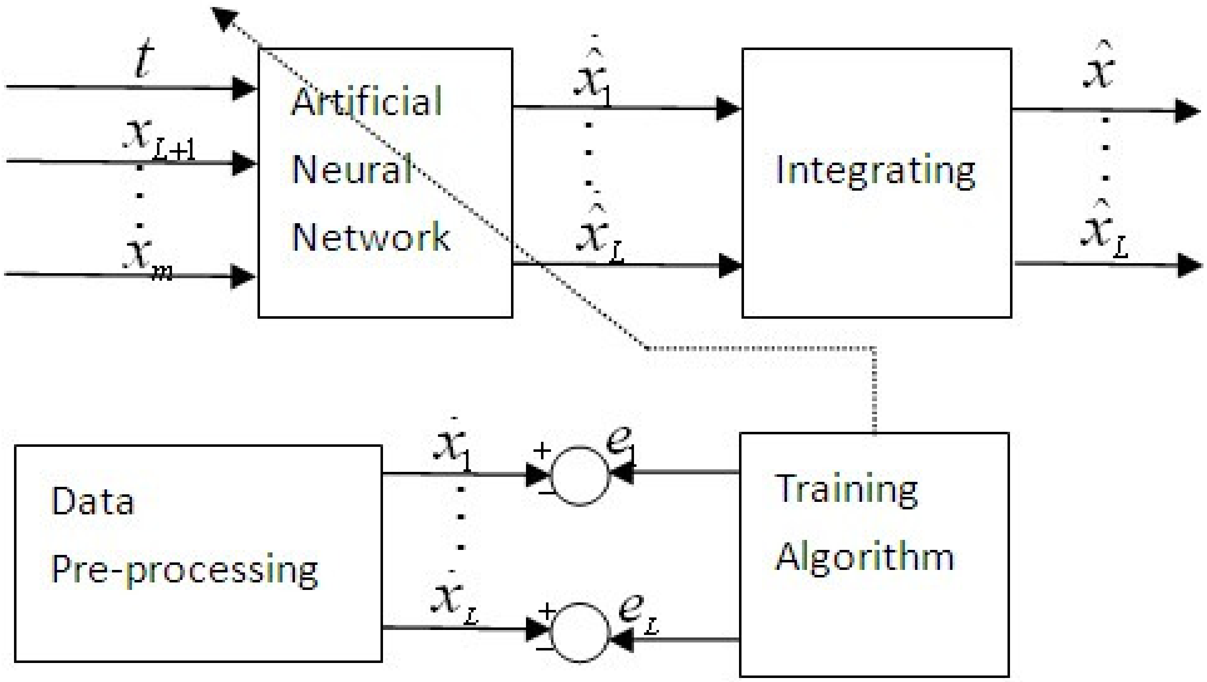

Figure 1. The flow diagram of the novel SS-ANN.

samples.

When ANN was trained well, there exist a set of data

$$P^{*} = (v_{ki}^{*}, w_{i}^{*}, w_{ij}^{*}, b_{i}^{*}) = \arg\{\sum_{i=1}^{L}\left\{\sum_{l=1}^{n}\left|\dot{x}_{i}^{l} - N_{i}(t_{l}, x_{L+1}^{l}, \cdots, x_{m}^{l}, P_{i})\right|^{p}\right\}^{\frac{1}{p}}\}$$

According to the approximation theory of ANN (Cybenko, 1989), given $e > 0$, the following formula is hold.

$$\left|\frac{dx_{k}}{dt} - N_{k}(t, x_{L+1}, \cdots, x_{m}, P^{*})\right| < e \tag{7}$$

Substituting Equation (5) into (7) gives

$$\dot{x}_{k} \approx N_{k}(t, x_{L+1}, \cdots, x_{m}, P_{i}^{*}) = \sum_{i=1}^{H} v_{ki}^{*} s[w_{i}^{*} t + (\sum_{j=L+1}^{m} w_{ij}^{*} x_{j}) + b_{i}^{*}] \tag{8}$$

Then x_{k} can be obtained approximately by integrating $\dot{x}_{k}$.

$$x_{k} = \int \dot{x}_{k} dt = \sum_{i=1}^{H} v_{ki}^{*} \int s[w_{i}^{*} t + (\sum_{j=L+1}^{m} w_{ij}^{*} x_{j}) + b_{i}^{*}]dt$$
$$k = 1, 2, \cdots, L \tag{9}$$

In accordance with aspects of the novel SS-ANN, the flow diagram is shown in the following Figure 1.

FERMENTATION PROCESS MODEL

It is difficult to establish the accurate mathematical model for erythromycin fermentation. A so-called gray box model based on its partial knowledge (Mark et al., 1996; Dai et al., 2006) has been used and can be described as the following form. The meaning of the symbols refers to Table 1.

$$\begin{cases} \frac{dX}{dt} = \mu * X - \frac{X}{V}\frac{dV}{dt} \\ \frac{dS}{dt} = -\sigma * X + \frac{S_{fc0}}{V} f_{c} - \frac{S}{V}\frac{dV}{dt} \\ \frac{dP}{dt} = \pi * X - K * X - \frac{P}{V}\frac{dV}{dt} \\ \frac{dC_{L}}{dt} = -\eta * X + K_{La}(C_{L}^{*} - C_{L}) - \frac{C_{L}}{V}\frac{dV}{dt} \\ \frac{dpH}{dt} = \psi * X + \frac{S_{fnh0} f_{nh} - S_{fyo} f_{y} - S_{fco} f_{c}}{V} - \frac{pH}{V}\frac{dV}{dt} \\ \frac{dV}{dt} = f_{c} + f_{p} + f_{nh} + f_{y} + f_{w} \end{cases} \tag{10}$$

EXPERIMENTAL RESULTS ANALYSIS

Sample collected from fermentation process

The novel SS-ANN is applied in an erythromycin fermen-

Table 1. Main process variables of the fermentation stage.

Varible	Explaination
X **(g/l)**	Mycelia concentration
S **(g/100 ml)**	Sugar concentration
P **(u/ml)**	Chemical potency
C_L **(g/l)**	Dissolved oxygen concentration
C^*_L **(g/l)**	Dissolved oxygen saturation concentration
pH	Zymotic fluid pH value
V **(l)**	Zymotic fluid volume
K **(h^{-1})**	Erythromycin hydrolysis rate constant
S_{fc0}, S_{fnh0},	Constant
S_{fy0}, K_{La}	Constant
f_c **(l/h)**	Dextrin flow rate
f_y **(l/h)**	Oil flow rate
Fw **(l/h)**	Water flow rate
f_p **(l/h)**	Propanol flow rate
f_{nh} **(l/h)**	Aqua ammonia flow rate

μ,σ,π,η and ψ are real-value uncertain functions of X,S,P and C_L. Where all kinds of flow rate f_c, f_y, f_w, f_p and f_{nh} are the process inputs. X, S, P, C_L, pH and V are the process dynamic variables which could be divided into two groups: the directly measurable group (C_L, pH, V) measured by chemical or physical sensors, and the directly immeasurable group(X, S, P).

tation process to estimate mycelia concentration X, sugar concentration S and chemical potency P on-line. We choose a 20-ton-fermentor in Zhenjiang Pharmaceutical factory of China as the experiment object. The whole erythromycin fermentation process lasts a period of 180 h. We sampled the field data C_L,pH,V, f_c, f_y, f_p, f_w, f_{nh}, with chemical and physical sensor and acquire X,S,P through off-line analyzing every 6 h.

ANN training

According to the fermentation process model, a feed-forward ANN was established as 9×20×3 with its input is selected as $(t, C_L, pH, V, f_c, f_y, f_p, f_w, f_{nh})^T$ and its desired output is $(\dot{X}, \dot{S}, \dot{P})^T$ which is obtained by using 5-points numerical derivative method.The topology structure is as shown in Figure 2. In order to improve the generalization of soft sensor model, the time variable t is added to the input which is different from the general SS-ANN. The sample data can be classified into two parts: Training data and test data. Seven batches are used as training data sets, and another three batches are used as test data sets .The training process of ANN is as same as mentioned in novel soft sensor modeling method. After iteratively training the ANN 300 times, the ultimate training error is reduced to 0.00009852. Both weight and bias values of the well-trained ANN were saved to develop the soft sensor model later.

Test results

The estimated values are obtained as Equation (9) mentioned in novel soft sensor modeling method. The test data sets are used to validate the novel soft sensor model. For simplicity, only the second batch experimental results are shown in Figures 3, 4 and 5. The estimated values are fitted and smoothed by least square fitting method in 5-minute-step.

It can be seen that the novel soft sensor model does not only provide good estimate of actual values but it also captures the dynamic behavior of them. Especially, the approximate ability of the novel model is better than the general SS-ANN when the process variables change rapidly as shown in Figures 4 and 5.

To show the superiority of the novel soft sensor model, more work is done in the following analysis. Maximum relative error (*MRE*), maximum absolute error (*MAE*) and mean squared error (*MSE*) are generally employed to evaluate the performance of a soft sensor model as shown in Tables 2, 3 and 4. The off-line analyzing values X, S, P are denoted as y_1, y_2, y_3 and the estimated values are denoted as $\bar{y}_1$, $\bar{y}_2$, $\bar{y}_3$. They are defined as following:

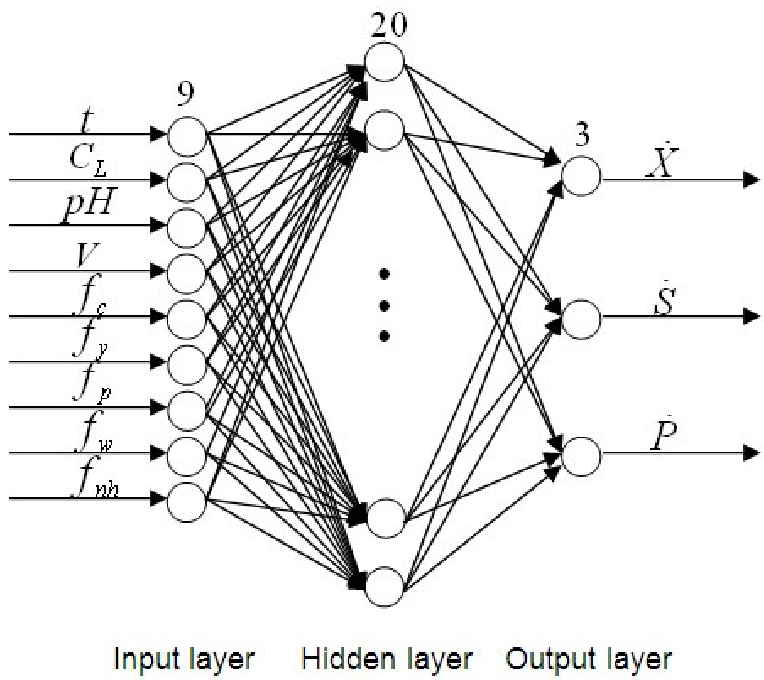

Figure 2. The topology structure of the established BP ANN with three layers.

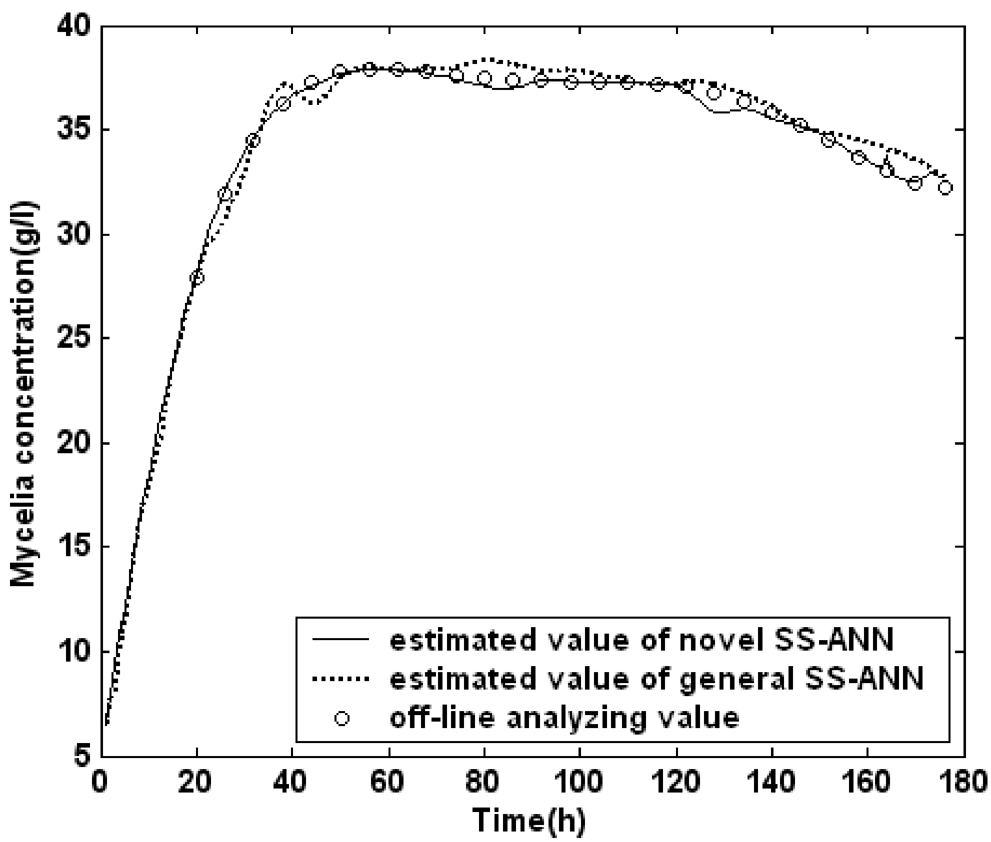

Figure 3. Comparison between estimated values and off-line analyzing values about mycelia concentration.

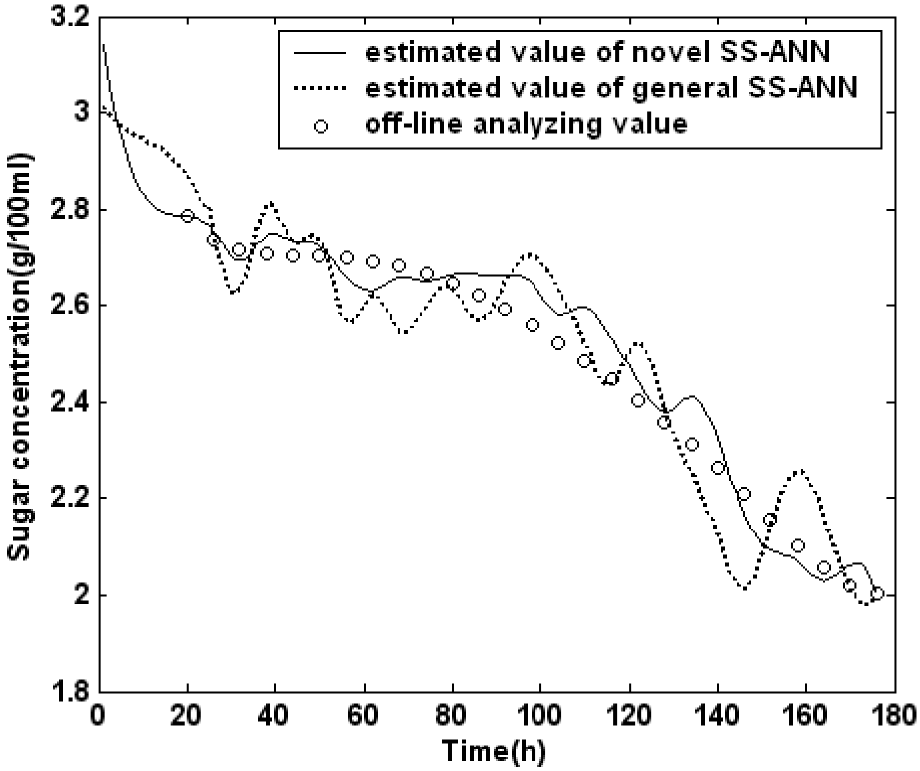

Figure 4. Comparison between estimated values and off-line analyzing values about sugar concentration.

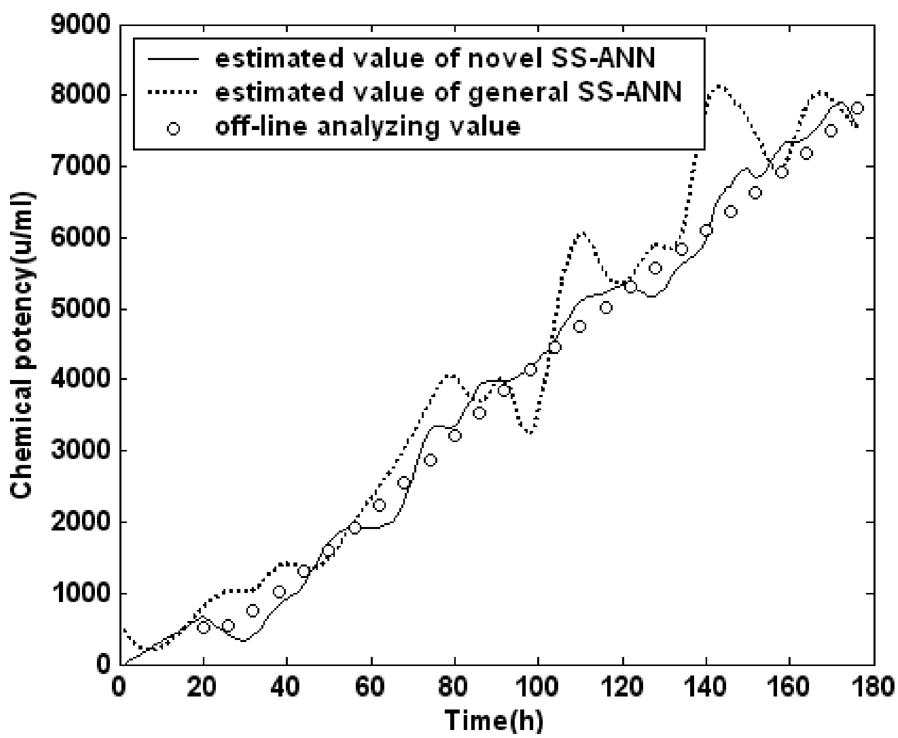

Figure 5. Comparison between estimated values and off-line analyzing values about chemical potency.

Table 2. The statistical result of estimated values for mycelia concentration.

Number	Novel SS-ANN			General SS-ANN		
	MRE	MAE	MSE	MRE	MAE	MSE
1	0.0230	0.5673	0.0585	0.0845	2.1148	0.9213
2	0.0244	0.8970	0.0615	0.1423	1.3411	0.3176
3	0.0358	0.7549	0.0692	0.2041	1.0426	0.4784

MRE, Maximum relative error; MAE, maximum absolute error; MSE, mean squared error.

Table 3. The statistical result of estimated values for sugar concentration.

Number	Novel SS-ANN			General SS-ANN		
	MRE	MAE	MSE	MRE	MAE	MSE
1	0.0321	0.0985	0.0028	0.1042	0.3605	0.0285
2	0.0454	0.1123	0.0031	0.1802	0.4328	0.0291
3	0.0543	0.1466	0.0035	0.2403	0.5286	0.0301

MRE, Maximum relative error; MAE, maximum absolute error; MSE, mean squared error.

Table 4. The statistical result of estimated values for chemical potency.

Number	Novel SS-ANN			General SS-ANN		
	MRE	MAE	MSE	MRE	MAE	MSE
1	0.0187	327.5	19856	0.6534	586.4	30856
2	0.0275	363.4	20994	0.7579	596.1	30297
3	0.0255	410.3	22453	0.5247	402.5	21352

MRE, Maximum relative error; MAE, maximum absolute error; MSE, mean squared error.

$$MRE = \max(\frac{\left|y_i^l - \bar{y}_i^l\right|}{y_i})$$

$$MAE = \max(\left|y_i^l - \bar{y}_i^l\right|)$$

$$MSE = \frac{\sum_{l=1}^{n}(y_i^l - \bar{y}_i^l)^2}{n} \qquad i = 1, 2, 3.$$

Where, l is the number of samples.

According to the Tables 2, 3 and 4, every indicator of the three criterions of the proposed novel model based on ANN is superior to the general SS-ANN. It illustrates that the novel model has a better performance than the general one. As a whole, the results show that the novel soft sensor model is appropriate for actual application.

Conclusion

A novel soft sensor model based on ANN is proposed and used to estimate mycelia concentration, sugar concentration and chemical potency in erythromycin fermentation process. By analyzing a grey-box model of fermentation process, the secondary variables are selected. ANN is established to approximate the function relation between measurable variables and the derivative of immeasurable variables, and then the estimated values is obtained by integrating the output expression of well-trained ANN. It must be noted that the selection of secondary variables is the most important, or else it is difficult to assure the convergence of ANN. The dynamic characteristic of the process is considered, the novel model improves the estimation accuracy and generation ability. The novel SS-ANN model has better performance than general SS-ANN model. It can be concluded that the soft sensor model mentioned in this paper is reasonable and effective.

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REFERENCES

Assis AJ, Filho RM (2000). Soft sensors development for on-line

bioreactor state estimation. Comput. Chem. Eng, 24: 1099-1103.
Bo CM, Li J, Sun CY, Wang YR (2003). The application of neural network soft sensor technology to an advanced control system of distillation operation. IJCNN, 2: 1054-1058.
Cheruy A (1997). Software sensors in bioprocess engineering. J. Biotechnol. 52: 193-199.
Cybenko G (1989). Approximation by super positions of a sigmoidal function. Math. Control. Signal. 2: 304-314.
Dai XZ, Wang WC, Ding YH, Sun ZY (2006). 'Assumed inherent sensor' inversion based ANN dynamic soft-sensing method and its application in erythromycin fermentation process. Comput. Chem. Eng. 30:1203-1225.
Gee DA, Ramirez WF (1996). On-line state estimation and parameter identification for batch formation. Biotechnol. Progr. 12: 132-140.
Gulnur B, Cenk U (2002). A modular simulation package for fed-batch fermentation: penicillin production. Compu. Chem. Eng. 26: 1553-1565.
Kesavan P, Lee JH, Saucedo V, Krishnagopalan GA (2000). Partial least squares (PLS)based monitoring and control of batch digesters. J. Process Control. 10: 229-236.
Mark RW, Jarmila G, Gary AM, Bo K(1996). On data-based modeling techniques for fermentation processes. Process Biochem. 31: 147-155.
Petr K, Bogan G, Sibylle S (2009). Data-driven soft sensors in the process industry. Comput. Chem. Eng. 33: 795-814.
Susan L, Luopa J, Zhu YH (1997). Neural networks as 'software sensors' in enzyme production. J. Biotechnol. 52: 257-266.
Vapnik V (1995). The nature of statistical learning theory. Springer New York Inc, New York, USA.