A METHOD OF DEVELOPING SOFT SENSOR MODEL USING FUZZY NEURAL NETWORK

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ABSTRACT

Soft sensor is an effective method to deal with the estimation of variables, which are difficult to measure because of the reasons of economy or technology. Fuzzy logic system can be used to develop the soft sensor model by infinite rules, but the fuzzy dividing of variable sets is a key problem to achieve an accurate fuzzy logic model. In this paper, we proposed a new method to develop soft sensor model based on fuzzy neural network. First, using a novel method to divide the variable fuzzy sets by the process input and output data. Second, developing the fuzzy logic model based on that fuzzy set dividing. After that, expressing the fuzzy system with a fuzzy neural network and getting the initial soft sensor model based FNN. Last, adjusting the relative parameters of soft sensor model by the BP learning method. The effectiveness of the method proposed and the preferable generalization ability of soft sensor model built are demonstrated by the simulation.

1 INTRODUCTION

In most of the process industries, there are often some significant variables that are difficult to measure but closely relevant to the product quality and need to be controlled strictly. In these cases, soft sensors work satisfactorily. Soft sensor technique is to achieve primary variables using multiple secondary measurements. However, there are no explicit physical relations between primary variables and secondary measurements for complicated process. So we cannot express them by a clear formula.

Artificial neural network (ANN) has been applied to develop soft sensor models effectively (e. g., Martin, 1997; Jinjun Wang and Shuqing Wang, 1996). ANN simulates intuitive thought of human being and has the characteristics such as distributed storage of information and parallel calculating and adaptive learning, *etc.* Like ANN, fuzzy logic (FL) can approximate arbitrary functions using finite rules and insensitive to system disturbance. So, it also has wide applications in modeling and prediction technology (Hao Zhang and Jie Wu and Bin Yu, 1999; Wenbiao Zhu and Zengqi Sun and Weiji Chen, 2001).

Reasonable fuzzy dividing of input and output space is the key point to get accurate fuzzy logic models. Aiming at this problem, the article proposed a novel method to divide variable fuzzy sets using process data. And based on this the FL system was developed combined with Wenbiao zhu's method (2001) of adaptive FL rule learning method. After that, the initial soft sensor model based on fuzzy ANN (FNN) is developed. Lastly, the relative parameters of initial model are adjusted through BP learning method so that we achieve the accurate soft sensor model.

2 PROBLEM FORMULATION

Consider a data set comprising N secondary measurements, $\mathbf{X}_{N\times m}$, and corresponding N primary variables, $\mathbf{Y}_{N\times 1}$, where N defines the number of observations. The final objective is to develop the soft sensor model:

$$y = f(x_1, x_2, \cdots, x_m) \tag{1}$$

In this article, we use the fuzzy rule model as (2) to express the FL system.

$$\begin{aligned} R_l: & \textit{if } x_1 \textit{ is } A_1^l, x_2 \textit{ is } A_2^l, \cdots, x_m \textit{ is } A_m^l \\ & \textit{then } y = B^l, \quad l = 1,2,\cdots,r \end{aligned} \tag{2}$$

Where, A_i^l defines the fuzzy set (FS) of the ith $(1 \le i \le m)$ secondary measurement x_i in the lth $(1 \le l \le r)$ rule; B^l defines the FS of the primary variable y in the lth rule; and r defines the number of fuzzy rules.

The degree of the reasonability in dividing FSs will affect the accuracy of approximating the arbitrary functions using the FL system. Too coarse dividing brings degressive precision, while too delicate dividing brings lowered speed in prediction because of the overmany fuzzy rules. It is obvious that the proper partition of FSs is the key problem to achieve accurate FL system.

3 DEVELOPMENT OF INITIAL FL SYSTEM

In this section, a new method of fuzzy partition of variables is first proposed and then the corresponding FL system is given combining with the adaptive FL rules learning method by Wenbiao zhu (2001).

To develop a FL system, we should divide the fuzzy sets of variables first. The usual means is to classify the set into big, middle and small or very big, big, middle, small and very small or more delicate. But it is difficult to determine the delicate or coarse degree of fuzzy sets so that the correct dividing cannot be achieved.

RPCL (Rival-Penalize Competitive Learning, Lei Xu, el. 1993) is an advanced method for clustering analysis. Its basic idea is that for each input not only the winner unit is modified to adapt to the input, but also its rival (the 2nd winner) is delearned by a smaller learning rate. It avoided the "dead-unit" problem of CL (Competitive Learning) and the crucial "redundant-unit" problem of FSCL (Frequency Sensitive Competitive Learning), So that it can allocate the data set into an appropriate number of units according to the property of the data. This predicated that if partitioning the fuzzy sets using RPCL, we could avoid the dividing neither too delicate nor too coarse.

3.1 The FS Partition of Primary Variable

The first step is to classify the primary variables y into a number of classes, p, using rival penalized competitive learning (RPCL) for clustering analysis. Second, calculate the center of every class respectively:

$$\bar{y}^i = (\sum_{j=1}^{n^i} y^{ij}) / n^i, y^{ij} \in C^i, i = 1, \cdots, p \tag{3}$$

Where $\bar{y}^i$ defines the center of the ith $(1 \le i \le p)$ class C^i; y^{ij} defines the jth data in the ith class; and n^i defines the number of primary variables belonging to the class C^i.

The p classes are corresponding to the p fuzzy sets $B^1, \cdots, B^p$. And the p centers are corresponding to the centers of the p fuzzy sets respectively.

3.2 The FS Partition of Secondary Variables

Like the classification of primary variables, classify secondary variables $x_k\, (k = 1, \cdots, m)$ into a number of classes, q_k, then calculating the center of every class respectively:

$$\bar{x}_k^i = (\sum_{j=1}^{n_k^i} x_k^{ij}) / n_k^i, x_k^{ij} \in C_k^i, k = 1, \cdots, m, i = 1, \cdots, q_k \quad (3)$$

Where $\bar{x}_k^i$ defines the center of the ith ($1 \le i \le q_k$) class C_k^i of secondary measurements of kth-dimension; x_k^{ij} defines the jth secondary variable x_k in the ith class C_k^i; and n_k^i defines the number of secondary variables belonging to the class C_k^i.

The q_k classes are corresponding to the q_k fuzzy sets $A_k^1, \cdots, A_k^{q_k}$ of kth dimension secondary variables. And the q_k centers of the classes are corresponding to the centers of the q_k fuzzy sets respectively.

The degree of membership of x_k belonging to A_k^i is:

$$\mu_{A_k^i}(x_k) = \exp[-(x_k - \bar{x}_k^i)^2 / \sigma_{A_k^i}^2], k = 1, \cdots m, i = 1, \cdots n_k^i \quad (4)$$

3.3 Development of FL System

In this section, the development of FL system will be described using the method of adaptive learning (Wenbiao zhu, 2001) combined with the above method of partition of fuzzy sets.

Step 1: Choose a data $(x_1, x_2, \cdots, x_m, y)$ from the initial data set.

Step 2: Develop a rule using this data.

Based on the above partition method of fuzzy sets, we select the A_k^i in which $x_k (k = 1, \cdots, m)$ gets the largest membership degree as the conditional language variable of x_k in the rule.

The $B^j (1 \le j \le p)$ to which y belongs is selected as the conclusion of this rule.

Step 3: Endow this rule a credible degree:

$$w_l = \mu_{A_1^{l_1}}(x_1) \times \mu_{A_2^{l_2}}(x_2) \times \cdots \times \mu_{A_m^{l_m}}(x_m) \quad (5)$$

Where, $1 \le l_k \le q_k$, l defines the Number of the rule.

Step 4: Verify the consistency of the rule.

Compare this rule with all foregone rules. If two rules are of the same condition but different conclusion, keep the rule of bigger credible degree and delete the other. Otherwise, put this rule into the fuzzy rule sets.

Step 5: The above steps are repeated until all the data are chosen.

After getting the fuzzy rule sets, the FL system owning the ability of soft sensor is achieved. The result of soft sensor is:

$$\hat{y} = (\sum_{l=1}^{r} \omega_l \bar{y}^l) / \sum_{l=1}^{r} \omega_l$$

$$= \sum_{l=1}^{r} \bar{y}^l \{\prod_{k=1}^{m} \exp[-(\frac{x_k - \bar{x}_k^l}{\sigma_{A_k^{l_k}}})^2]\} / \sum_{l=1}^{r} \{\prod_{k=1}^{m} \exp[-(\frac{x_k - \bar{x}_k^l}{\sigma_{A_k^{l_k}}})^2]\} \quad (6)$$

Where, ω_l is the credible degree of the lth rule; $\bar{y}^l$ is the center of the conclusion of the lth rule.

4 SOFT SENSOR MODEL BASED ON FNN

4.1 The Structure of FNN Model

The FL system above can be expressed as fuzzy neural network (FNN). The structure of the soft sensor model based on FNN is shown in figure 1.

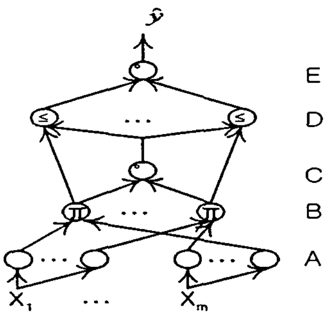


Figure 1 the structure of soft sensor model based on FNN

In figure 1, $\hat{y}$ is the prediction result of the soft sensor; $\mathbf{x} = (x_1, \cdots, x_m)$ are the secondary variables. Furthermore, layer A is the fuzzy layer of input data; B is similar to a multiplier, and its output is the credible degree of the r rules respectively. Layer C, D, E finish the work of formula (6) together, and the weigh of link is all 1 from layer C to E.

4.2 the Adjust of Soft Sensor Model Parameters

For the initial FNN model, we adopt the BP learning method based on descendant gradient to adjust the center of fuzzy subsets of the input and output data, and the breadth of fuzzy subsets of the input data.
The selected target function is:

$$e(k') = (\hat{y}(k') - y_d)^2 / 2 \tag{7}$$

Where, $\hat{y}(k')$ defines the output of the fuzzy model of the k' th iteration. The usual formula of BP learning method is:

$$\theta(k'+1) = \theta(k') - \alpha \left.\frac{\partial e(k')}{\partial \theta}\right|_{\theta=\theta(k')} \tag{8}$$

Where, α is the rate of learning; k' the order of iteration. From (7), (8), we have:

$$\theta(k'+1) = \theta(k') - \alpha(\hat{y}(k') - y_d) \left.\frac{\partial \hat{y}(k')}{\partial \theta}\right|_{\theta=\theta(k')} \tag{9}$$

From (6), we have:

$$\frac{\partial \hat{y}(k')}{\partial \bar{y}_l(k')} = \mu_l(k') / \sum_{l=1}^{r} \mu_l(k') \tag{10}$$

$$\frac{\partial \hat{y}(k')}{\partial \mu_l(k')} = \frac{(\bar{y}_l(k') - \hat{y}(k'))}{\sum_{l=1}^{r} \mu_l(k')} \tag{11}$$

Where,

$$\mu_l(k') = \prod_{k=1}^{m} \exp\left[-\left(\frac{x_k - \bar{x}_k^l(k')}{\sigma_{A_k^l}(k')}\right)^2\right] \tag{12}$$

From (12), we have:

$$\frac{\partial \mu_l(k')}{\partial \bar{x}_k^l(k')} = \mu_l \cdot \frac{2(x_k - \bar{x}_k^l(k'))}{(\sigma_k^l(k'))^2} \tag{13}$$

$$\frac{\partial \mu_l(k')}{\partial \sigma_{A_k^l}(k')} = \mu_l \cdot \frac{2(x_k - \bar{x}_k^l(k'))^2}{(\sigma_{A_k^l}(k'))^3} \tag{14}$$

From (11) ~ (14), we will have:

$$\frac{\partial \hat{y}(k')}{\partial \bar{x}_k^l(k')} = \frac{\mu_l(k')}{\sum_{l=1}^{r} \mu_l(k')} \cdot (\bar{y}_l(k') - \hat{y}(k')) \cdot \frac{2(x_k - \bar{x}_k^l(k'))}{(\sigma_{A_k^l}(k'))^2} \tag{15}$$

$$\frac{\partial \hat{y}}{\partial \sigma_{A_k^l}} = \frac{\mu_l}{\sum_{l=1}^{r} \mu_l} \cdot (\bar{y}_l - \hat{y}) \cdot \frac{2(x_k - \bar{x}_k^l)^2}{(\sigma_{A_k^l})^3} \tag{16}$$

Combined (9) with (10), (15), (16), the parameters of soft sensor based on FNN can be adjusted.

5 RESULT OF SIMULATION

The simulated process is the adiabatic continuous first-order exothermic reaction in a continuous stirred-tank reactor (CSTR). The input of this process is pure A and the desired product is R. The system is simulated by the following coupled ordinary differential equations (Economou et al. 1986).

$$\begin{aligned} \frac{dR_0}{dt} &= \frac{R_i - R_0}{\tau} + k_1(1 - R_0) - k_{-1} R_0 \\ \frac{dT_0}{dt} &= \frac{\Delta H_R}{\rho C_P}(k_1(1 - R_0) - k_{-1} R_0) + \frac{T_i - T_0}{\tau} \end{aligned} \tag{17}$$

Where

$$k_1 = c_1 \exp(\frac{-Q_1}{RT_0})$$

$$k_{-1} = c_{-1} \exp(\frac{-Q_{-1}}{RT_0})$$

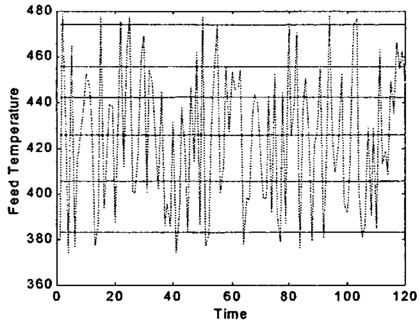
It is desired to predict the concentration of product R using the given temperature of feed stream T_i and the reactor's temperature T_0. So, the feed temperature T_i and the reactor's temperature T_0 were selected as secondary variables, and the concentration of product R is the primary variable. We want to develop the model between T_i, T_0 and R. A method similar to that in Dasaratha *et al.* (1996) was used to generate data set for developing and verifying model. The Steady state operating point and the process parameters are given in table 4.

τ	60s
c_1	$5\times10^3 s^{-1}$
c_{-1}	$1\times10^6 s^{-1}$
Q_1	$10{,}000\, cal\ mol^{-1}$
Q_{-1}	$15{,}000\, cal\ mol^{-1}$
R	$1.987\, cal\ mol^{-1}\cdot K^{-1}$
ΔH_R	$5{,}000\, cal\ mol^{-1}$
ρ	$1 kg / g$
C_P	$1{,}000\, cal\cdot kg^{-1}\cdot K^{-1}$
R_0	0.508mol/L
T_0	430K
T_i	427K

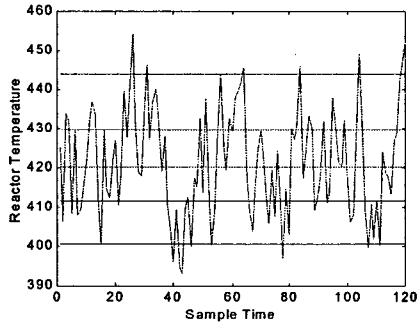
Table 4 Constants and Steady-State Operating Conditions for CSTR

Using above method, data sets of size 120, 80 were collected with feed temperature T_i varying randomly with a uniform distribution within 12.5% of the steady-state operation point 427K. Where, data set of size 120 is used as learning data, the other is used as testing data. The time-series plot of realization of the data is shown in Figure 2(a), 2(b) and 2(c).

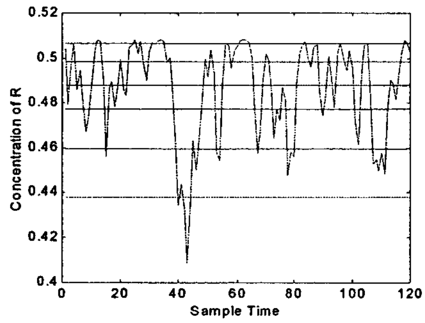
In Figure 2, the Y-coordinate values of horizontal lines are the values of clustering centers after classification analysis of RPCL to feed temperature, reactor' temperature and concentration of product R.



2(a) Feed temperature sequence



2(b) Reactor' temperature sequence



2(c) Concentration response of CSTR

Figure 2 the learning data set and the centers After classification

Before classification to the variables, 7 initial centers were given to every variable' data set respectively. Figure 2 shows that RPCL excluded the redundant centers, there are 6, 5 and 6 centers for feed temperature, reactor's temperature and concentration of product R data sets respectively, so that we got a reasonable classification according to the property of the data and achieved an appropriate variable sets dividing. Then, developed the FL system using the method described in **3.3** and expressed it with a FNN so that we could get the initial soft sensor.

After developed the initial soft sensor based on FNN, we use the BP learning method described in **4.2** to adjust the parameters of model properly. Lastly, apply the testing data to the soft sensor model built. The result of simulation is shown in Figure 3. And the MSE (Mean Squared Error) of estimation is 0.0051.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_d(i) - y_e(i))^2 \qquad (17)$$

Where, y_d is the desired value of primary variable, y_e the estimated value.

That result and Figure 3 all indicate that the model of soft sensor based on FNN supposed is effective.

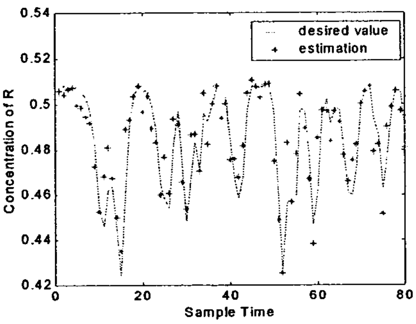


Figure 3 Simulation Result

6 CONCLUSION

In this work, a novel approach to dividing fuzzy sets has been supposed. This method makes the dividing of fuzzy sets neither too delicate nor too coarse, so we can get an accurate FL system. Conventional approaches cannot decide the delicate degree for the dividing of fuzzy sets effectively. This makes the estimation accuracy or estimation speed fall. Based on the method proposed, we described the development of FL system and soft sensor model based on FNN and the verifying method of parameters of soft sensor model.

Simulation shows that the method of development of soft sensor model based on FNN is effective.

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