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Prediction of Process Trends Based on Neural Networks

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Abstract In order to catch more process details in chemical processes, a dynamic model for prediction of process trends is proposed by modifying traditional time-series ANN (artificial neural networks) model with impulse response identification means. The application result of the model is briefly discussed.
Keywords time-series neural network, dynamic models

1 INTRODUCTION

In order to understand a process in more detail several means have been put forward. Stephanopoulos and Han[1] gave a precise mathematical framework in which a trend is stipulated as the "sequence of maximal scaling episodes, defined over time intervals, whose distinguished points are strictly ordered in time". Cheung and Stephanopoulos[2,3] gave a concise describing method, the episodic representation, for process trends at a qualitative, semiquantitative and quantitative level. Janusz and Venkatasubramanian[4] developed an analogous method. They presented four major elements to capture the important information in process trends: primitives, episodes, trends and profiles. Mah *et al.*[5] put forward a piecewise linear smoothing means for process trends. Bakshi and Stephanopoulos[6] adopted wavelet analysis into process data feature extraction. Stephanopoulos and Han[1] also pointed out that, "the key skill is the formation of a 'mental' model of the process operations that fits the current facts about the process and enables the operators to assess process behavior and predict the effects of possible control actions."

In this study, an improved ANN and time series based means is put forward to predict process trends quantitatively. It includes two parts: describe dynamic process and predict process trends.

2 DYNAMIC PROCESS MODEL BASED ON ANN

2.1 Review

The best representation of a dynamic process is from its mechanism. However, in many cases it is not easy to obtain and solve a dynamic mechanism model. Under such circumstances some non-mechanism models means have been put forward, and artificial neural network is one of them. Due to its nonlinear approximate capability, ANN is suitable for chemical process modelling[7–11]. For a given dynamic process, the most prominent feature is that the variables vary with time. However, for an ANN model it is difficult to introduce time t into the model as a variable. In order to use ANN to model a dynamic process, discrete time-series data are adopted in the model[12–14]. At time t, the input consists of $X_j(t)$, $X_j(t-\Delta t)$, $\cdots$, $X_j(t-N\Delta t)$, where $X_j(t)$ is the value of the jth process variable at time t, Δt is the time interval, and N is the number of successive data points of the process variable, which is given empirically. Its structure is illustrated in Fig. 1 (without impulse response coefficient). However, in previous research works[12–14], determination of the time-series length is mainly empirical. This makes the denotative application of time-series neural networks without guarantee.

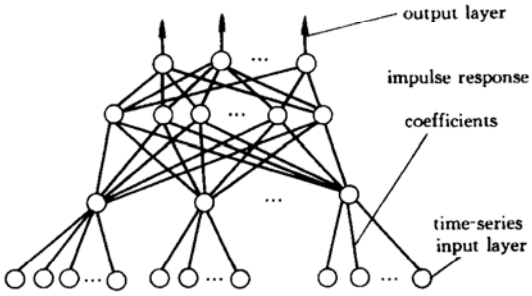

Figure 1 Structure of a modified ANN

2.2 Process characteristics

For a given controllable process, responding to the input impulse, the output has such a response curve as shown in Fig. 2. An impulse is at the process input side at time t_0 and a response can be detected at the output side at time t_d. After a period of t_s the system output returns to steady status. Thus in the period between t_d and t_s a series of discrete value of $h(t)$ can be detected. If sampling period is $\Delta\tau$, the system rehabilitating period N_l is $(t_s - t_d)/\Delta\tau$. As illustrated in Fig. 2, for a single in single out (SISO) system, the output at time t can be written as the following form

$$y_t - y_0 = \sum_{j=1}^{N} h_j x_{t-j} \tag{1}$$

where y_t is the measured value at time t and y_0 is the initial value. Eq. (1) indicates that to calculate the output value exactly it is necessary to add up all

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the inputs in N synchronously. In view of process causality, if time-series values of the input variable are adopted as ANN inputs, the time-series length should cover the rehabilitating period. However the previous researchers did not notice this fact[12-14].

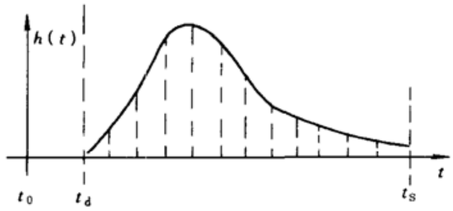


Figure 2 Impulse response curve

2.3 Dynamic process modeling based on modified ANN

For a process with m inputs and n outputs, the traditional ANN dynamic model can be written as

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = F\begin{pmatrix} x_{1,1},\ x_{1,2}, \cdots, x_{1,N_s} \\ x_{2,1},\ x_{2,2}, \cdots, x_{2,N_s} \\ \vdots \\ x_{m,1},\ x_{m,2}, \cdots, x_{m,N_s} \end{pmatrix} \tag{2}$$

where $F(.)$ is the mapping function between process inputs and outputs, $x_{i,j}(i=1,\cdots,m, j=1,\cdots,N_s)$ is the jth time-series value of the ith input variable, $y_i(i=1,\cdots,n)$ is the ith output variable, and N_s is the chosen time-series length. With process causality, N_s equals to system rehabilitating period N_l. In general, N_l is not a small value. If all the time-series values N_l were adopted in an ANN model, the ANN structure would become very complicated. To avoid the problem the system impulse response coefficients are introduced into the time-series ANN model. It is

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = F\begin{pmatrix} x_{1,1}h_{1,1},\ x_{1,2}h_{1,2}, \cdots, x_{1,N_1}h_{1,N_1} \\ x_{2,1}h_{2,1},\ x_{2,2}h_{2,2}, \cdots, x_{2,N_2}h_{2,N_2} \\ \vdots \\ x_{m,1}h_{m,1},\ x_{m,2}h_{m,2}, \cdots, x_{m,N_m}h_{m,N_m} \end{pmatrix} \tag{3}$$

where $h_{i,j}(i=1,\cdots,m; j=1,\cdots,N_i)$ is the jth impulse response coefficient of the ith variable, N_i is the impulse response period of the ith variable, and $F(.)$ represents the neural network. The structure of the modified ANN is illustrated in Fig. 1. The weights, which connect the first hidden layer and the time-series input layer, are replaced by impulse response coefficients that can be detected online or off-line. Thus the need-to-trained unknown parameters decrease greatly without process information lost.

3 TRENDS PREDICTION

3.1 Trends predictive model based on ANN

There exists high causality among the process variables that provide proper circumstance for causal prediction. This new means for trends prediction is based on the process causality. Generally the system status is denoted by one of the process variables, the eigen-vector, and its trend represents the changing direction. So the multi-input single-output (MISO) process is discussed here only. In this paper, an ANN based modeling means is put forward to deal with the MISO process. If the relationship among variables is nonlinear, its one-step predicting output model can be written as

$$\begin{cases} Y_{k+1} = F(y_{k+1,1},\ y_{k+1,2}, \cdots, y_{k+1,m}) \\ y_{k+1,i} = y_{0,i} + \sum_{j=1}^{N} h_{j,i}x_{k-j+1,i} \quad i=1,\cdots,m \end{cases} \tag{4}$$

where $F(.)$ is the ANN mapping function between process output and input; Y_{k+1} is the one-step predicting value at time k, $y_{k+1,i}(i=1,\cdots,m)$ is the output variation caused by the ith input variable, and m is the number of the relative input variables. Eq. (4) represents that the gross output is the combination of the output caused by all inputs. On the basis of Eq. (4) the process output value of the lth step is

$$\begin{cases} Y_{k+l} = F(y_{k+l,1},\ y_{k+l,2}, \cdots, y_{k+l,m}) \\ \qquad\qquad l=1,2,\cdots N_s \\ y_{k+l,i} = y_{0,i} + \sum_{j=1}^{l} h_{j,i}\widehat{x}_{k+l-j,i} + \sum_{j=l+1}^{N} h_{j,i}x_{k+l-j,i} \\ \qquad\qquad i=1,\cdots,m \end{cases} \tag{5}$$

where $\widehat{x}_{i,j}$ is the ith step predicting value of the jth input variable, which is given by the next equation

$$\widehat{x}_{k+j,i} = F_m(\widehat{x}_{k+j-1,i},\ \widehat{x}_{k+j-2,i}, \cdots, \widehat{x}_{k+1,i}, x_{k,j}, \cdots, x_{k+j-N_{i-1,i}}) \tag{6}$$

Equation (6) indicates that $\widehat{x}_{k+j,i}$ is the function $F_m(.)$ which is the mapping function of the mth input variable and is obtained by ANN learning, of the last N_i time-series of the mth input variable, which comprises two segments: the predicted segment $(\widehat{x}_{k+j-1,i}, \cdots, \widehat{x}_{k+1,i})$ and the measured segment $(x_{k,i}, \cdots, x_{k+j-N_{i-1,j}})$.

3.2 Input variable prediction

Because it is difficult to obtain input variable values based on process causality, the usual way is using time-series model to calculate the unknown values.

There are two ways to calculate the future input values. One is keeping the future values equal to the last measured value but the error of prediction will become larger with the increase of the predicting step. Another way is using the history data to predict the future values. (The later way is adopted in this paper.) The time-series model is replaced by ANN model, which means that the ANN inputs are the time-series values of process inputs. The future value of input variables is calculated by one- step ANN predictive model. The disposing steps are: (1) Calculate the one step predictive data; (2) Replace the oldest data with the calculated predictive data to constitute a new input time-series; (3) Use the new time- series to predict the next input future value; (4) Repeat Step (1) to (3) under the pre-set predicting steps.

3.3 Computational procedure

The application of the predictive model follows the next steps (the current time is k):

(1) Predict the input variable value of the next step using trained ANN $F_i(.)$;

(2) Combine the new computed input value with the previous $N_i - 1$ input time-series values to form a new time-series;

(3) Introduce the new input time-series to the time-series input layer, and the weights of the first hidden layer are the impulse response coefficients;

(4) Predict the output value of the next step through Eq. (5);

(5) Repeat Step (1) to (4) according to the pre-set predicting step.

4 CASE STUDY

4.1 Case description

The stripper of Tennessee Eastman problem[15,16] is treated to illustrate the above predictive method. Fig. 3 shows a diagram of its basic control system. Stripper temperature is chosen as the system eigenvector, *viz.* the trends prediction parameter. There are four control variables in the process: flowrates of Stream 4 and Stream 10, reboiler steam and bottom stream. Because the steam flow is controlled by the temperature, it can not be an input variable of the model. The bottom stream has little influence on stripper temperature. As a result, there are two input variables in the predictive model: flows of Stream 4 and Stream 10.

4.2 Computational procedure and results

Process disturbances were added to Stream 4 and Stream 10 to generate the process dynamic data. Process signal noise still exists in the measured data.

First, the impulse response is detected. The impulse response curves corresponding to the two input variables are shown in Fig. 4. The rehabilitating period caused by Stream 4 is set as 330 s and that caused by Stream 10 is 125 s. The time-delay periods of the two input variables are 3 s.

Second, the dynamic process model is constructed. To model the process with Eq. (3), flowrates of stream 4 and stream 10 are taken as the ANN inputs and stripper temperature is the ANN output. The training and testing samples are both 200 groups. After optimization the ANN structure is chosen as follows: input time-series points are 330 and 125, the two hidden layer nets are 2 and 4 respectively, and the transfer functions are all linear. The testing results are shown in Fig. 5. The training and testing average variance are 2.696×10^{-5} and 4.32×10^{-5}.

The two input variables in the one-step ANN based predictive model are also trained. The ANN structure is shown in Table 1.

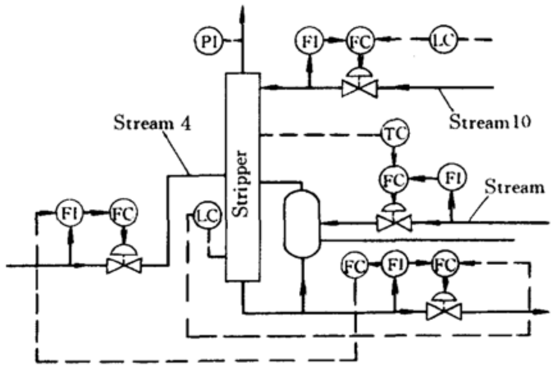
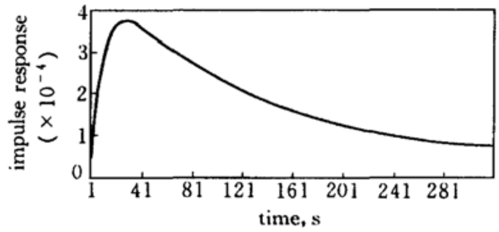
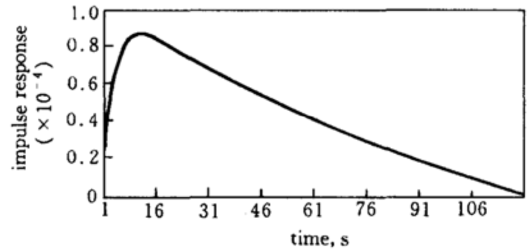


Figure 3 Base control system of the stripper



(a) Output impulse response corresponding to Stream 4



(b) Output impulse response corresponding to Stream 10

Figure 4 Output impulse response curves

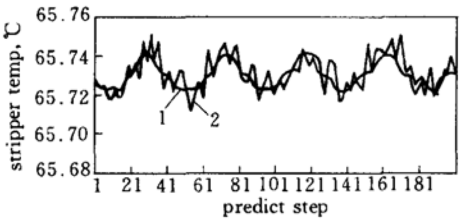


Figure 5 Testing result of dynamic process ANN model

1—calculated data; 2—measured data

Table 1 ANN structure

ANN	Nets	Transfer function
1	10-2-1	sigmoid-linear
2	10-3-1	sigmoid-linear

where ANN 1 is corresponding to input variable Stream 4 and ANN 2 is corresponding to Stream 10.

Third, the trained ANN model is need to predict the process trends according to Section 3.3. In this case 100 samples and 100 predictive steps per sample are inspected. The predicted result is shown in Figs. 6 and 7. Fig. 6 illustrates the total predicted error varied with predicted steps. Fig. 7 shows the comparison of the predicted curve and measured curve for three variables (flowrate of Stream 4, flowrate of Stream 10 and the stripper temperature) while the samples are stochastically cited. Fig. 7 shows that, though the measured data mix with signal noise, the model can still predict the overall process trends.

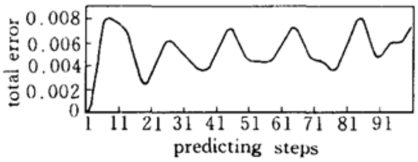
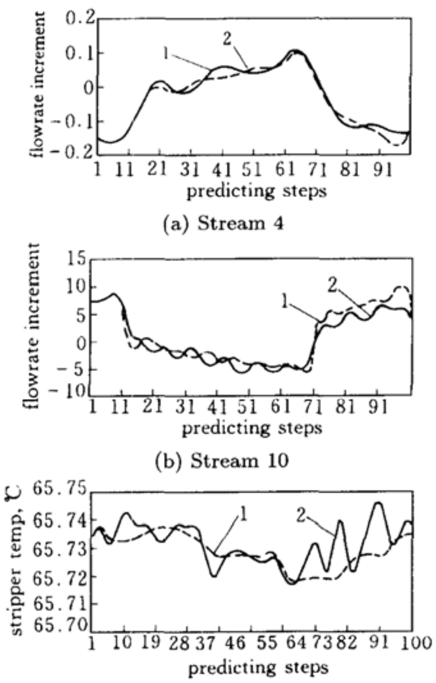


Figure 6 Distribution of total predicted error

5 CONCLUSIONS

A modified time-series ANN model is put forward based on the process characteristics. Compared with traditional ANN dynamic model, this model has a simpler structure but express the process without information loss. Based on the above ANN model, a dynamic model is put forward. This model includes two parts: the predictive model of input variables and the predictive model of output variables. The case study shows that the predictive model bears the capability to predict the overall process trends under a relative long predictive time steps. This makes it possible to evaluate the process status and the effect of the operator's action.



(a) Stream 4

(b) Stream 10

(c) Stripper temperature

Figure 7 Comparison of predict value and measured value
1—predicted; 2—measured

NOMENCLATURE

$F(.)$	ANN mapping function
$F_m(.)$	ANN mapping function of variable m
$h_{i,j}$	jth impulse response coefficient of the ith variable
N_l	impulse response rehabilitating period
N_s	time-series length
t_0	initial time
t_d	time-delay period
t_s	system rehabilitating time
$X_j(t)$	value of the jth process variable at time t
$x_{i,j}$	measured value of the ith step of the jth input variable
$\widehat{x}_{i,j}$	predicted value of the ith step of the jth input variable
Y_j	predict value of the jth step
y_0	initial output value
y_t	measured output value at time t
$y_{i,j}$	output variation caused by the jth input variable at time i
$\Delta\tau$	sample period

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