Soft Sensing Model Based on Mean Impact Value for Erythromycin Fermentation Process

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Abstract

A variable selection method based on mean impact value (MIV) is proposed to obtain an accurate soft sensing result of the key variables that cannot be measured online in the erythromycin fermentation process. The MIV method is used to calculated the contribution rate of input to key variables and the obtained contribution rate is consistent and stable. According to the MIV method, an optimized soft sensing model of erythromycin fermentation process is constructed and experimental result show that the input variables are fewer and the accuracy of the soft sensing model is higher than the traditional methods.

Keywords

Soft Sensing Model; Mean Impact Value (MIV); Erythromycin Fermentation Process.

1. Introduction

The biochemical fermentation process is typically highly non-linear, time-varying and lack of online measurement instrument for key biochemical variables[1], causing the automation level of the fermentation process much lower than that of other industrial processes. Real-time detection of the biochemical variables is the prerequisite for further control and optimization of the process, so it is of extreme practical significance to study online detection theory for crucial biochemical variables that conform to the requirements of industrial applications. Currently, due to the limitation of detecting equipment or technology, certain biochemical variables still cannot be detected effectively by sensors in real time[1]. In [2], researchers proposed an artificial neural network soft sensing method based on the "assumed inherent sensor" and its inversion concepts to estimate the crucial process variables. However, owing to the disturbance of redundant input variables in the dataset, the accuracy of this method is not high enough to satisfy the demand of closed-loop control. Nevertheless, redundant information may cause deterioration of the generalization ability and an increase of the computational cost[3]. Therefore, a variety of methods have been proposed to solve this problem[4-7]. Variable selection method is one of the effective methods[8, 9]. Variable selection method based on mean impact value (MIV) poses a simple, intuitionistic and understandable physical meaning and contribution rate calculated by this method features high stability[10, 11].

In this paper, we propose an MIV variable selection method based on the neural network structure, which calculated the contribution rate of each input variable according to its impact to the output variables. The experimental result in the erythromycin fermentation process shows that contribution rate calculated by this method has obvious difference among variables as well as high stability and precision. In general, this method is suitable for common input variable selection in building a simple soft sensing model.

2. Variable selection method based on mean impact value

Consider an independent input variable vector which contains p variables, observe it m times to get the variable space $X=[x_1 \quad x_2 \quad \cdots \quad x_m]^T$, and each dependent output variable corresponding to the sample point can be written as $Y=[y_1 \quad y_2 \quad \cdots \quad y_m]^T$. Taking independent variable vector X including

m samples as input, the corresponding output vector Y as output, we train the neural network, and then save the trained neural network. Give a 10% increase and 10% decrease respectively to a single independent variable at one time. In this way, $2p(i=1,\cdots p)$ new variable spaces can be obtained.

$$X_i^{(1)}=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1i}(1+10\%) & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2i}(1+10\%) & \cdots & x_{2p} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mi}(1+10\%) & \cdots & x_{mp} \end{bmatrix} \tag{1}$$

$$X_i^{(2)}=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1i}(1-10\%) & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2i}(1-10\%) & \cdots & x_{2p} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mi}(1-10\%) & \cdots & x_{mp} \end{bmatrix} \tag{2}$$

Take the newly-constructed variable spaces one by one as the input of the network model built previously, and $2p$ groups of output vector are obtained through the network. Each group is corresponding to the sample point whose *i-th* ($i=1,2\cdots p$) variable index is changed.

$$Y_i^{(1)}=\left[y_{i_1}^{(1)} \quad y_{i_2}^{(1)} \quad \cdots \quad y_{i_m}^{(1)}\right]^T \tag{3}$$

$$Y_i^{(2)}=\left[y_{i_1}^{(2)} \quad y_{i_2}^{(2)} \quad \cdots \quad y_{i_m}^{(2)}\right]^T \tag{4}$$

Calculate the difference of equations (3), (4) to obtain the impact value by the equation $IV_i=Y_i^{(1)}-Y_i^{(2)}$ when the *i-th* variable indicator is changed. And the mean impact value can be calculated as following:

$$MIV_i=\sum_{j=1}^{m} IV_i(j)/m \quad i=1,2,\cdots p \tag{5}$$

The symbol of MIV_i indicates the correlation between the independent variable and the dependent variable, whose value represents the relative importance of the independent variable on the dependent variable. Further, the overall contribution rate of x_i to y can be expressed as:

$$\alpha_{\mathrm{M}_i}=\frac{\mathrm{MIV}_i}{\sum_{i=1}^{p}\left|\mathrm{MIV}_i\right|} \tag{6}$$

Sort the input variables according to their contribution rate and delete the variables that pose little effect on output, thus the variable selection based on MIV is realized. More specifically, within the p input variables, if the sum of the contribution rate of s variables ($s<p$), $a=\sum_{i=1}^{s}\alpha_{M_i}\ge a^*$, it can be considered that these s variables are important while the other $p-s$ variables can be removed due to relatively small contribution , where a^* is a value close to 1, such as 0.9 or 0.95. The value of a^* selected in this paper is 0.95.

3. Construction of soft sensing model for erythromycin fermentation process

The experimental data used to construct and test the soft sensing model in this paper was acquired from a Zhenjiang pharmaceutical factory of China. The data include controllable variables such as dextrin volume, soybean oil volume, propyl alcohol volume, water volume and ammonia volume and measurable variables such as dissolved oxygen, pH value and volume; Key biochemical variables such as mycelia concentration, sugar concentration and chemical potency are also included.

According to literature [2], the soft sensing model is to estimate the variables that cannot be measured directly by using the directly measurable variables and their derivatives in order to satisfy the dynamic characteristics. For the erythromycin fermentation process, the soft sensing model can be obtained as follow:

$$\hat{x}=(\boldsymbol{z},\dot{\boldsymbol{z}},\ddot{\boldsymbol{z}},\cdots,\boldsymbol{u},\dot{\boldsymbol{u}},\ddot{\boldsymbol{u}}), \tag{7}$$

where $\boldsymbol{z}=\left[C_L, pH, V\right]^T$ are the directly measurable variables dissolved oxygen concentration, zymotic fluid pH value, and zymotic fluid volume, $\boldsymbol{u}=\left[V_c, V_y, V_p, V_w, V_{nh}\right]^T$ are respectively dextrin volume, oil volume, propanol volume, water volume and aqua ammonia volume. $\hat{x}=(X, S, P)^T$ are the mycelia concentration, sugar concentration and chemical potency. Therefor the initial soft sensing model of erythromycin can also be expressed as

$$\begin{cases} X=\varphi_1(\boldsymbol{z},\dot{\boldsymbol{z}},\ddot{\boldsymbol{z}},\cdots,\boldsymbol{u},\dot{\boldsymbol{u}},\ddot{\boldsymbol{u}}) \\ S=\varphi_2(\boldsymbol{z},\dot{\boldsymbol{z}},\ddot{\boldsymbol{z}},\cdots,\boldsymbol{u},\dot{\boldsymbol{u}},\ddot{\boldsymbol{u}}) \\ P=\varphi_3(\boldsymbol{z},\dot{\boldsymbol{z}},\ddot{\boldsymbol{z}},\cdots,\boldsymbol{u},\dot{\boldsymbol{u}},\ddot{\boldsymbol{u}}) \end{cases} \tag{8}$$

Here, we choose a 20 ton fermentor in Zhenjiang pharmaceutical factory of China as the experiment object to test the soft sensing method to estimate such biochemical variables in erythromycin fermentation process as mycelia concentration, sugar concentration and chemical potency, or *X*, *S*, *P*. The complete erythromycin fermentation process lasts a period of 180 hours or 7 days. For such a 180h-duration process, sample the field data ***z***, ***u*** every 5 min by chemical and physical sensors. Obtain 3 batches of data, 2 of which are used for neural network training while the remaining one is used for testing. Using these data, the most important input variables in the erythromycin fermentation process are sorted out and an optimized soft sensing model is established. Specific steps are as follows:

Step 1 Data processing.

For the sake of avoiding distortion, use wavelet transform to filter the experimental data; use the 7-point numerical derivation to obtain derivatives of input data.

Step 2 Establish neural network model.

A three-layer feedforward neural network of 24-40-3 structure is employed with "sigmoid" transfer activation on hidden layer and "linear" transfer function on output layer. Use BP algorithm to train the neural network 100 times in order to achieve satisfactory training precision. Save the neural network parameters.

Step 3 Calculate the contribution rate of input variables to input variables.

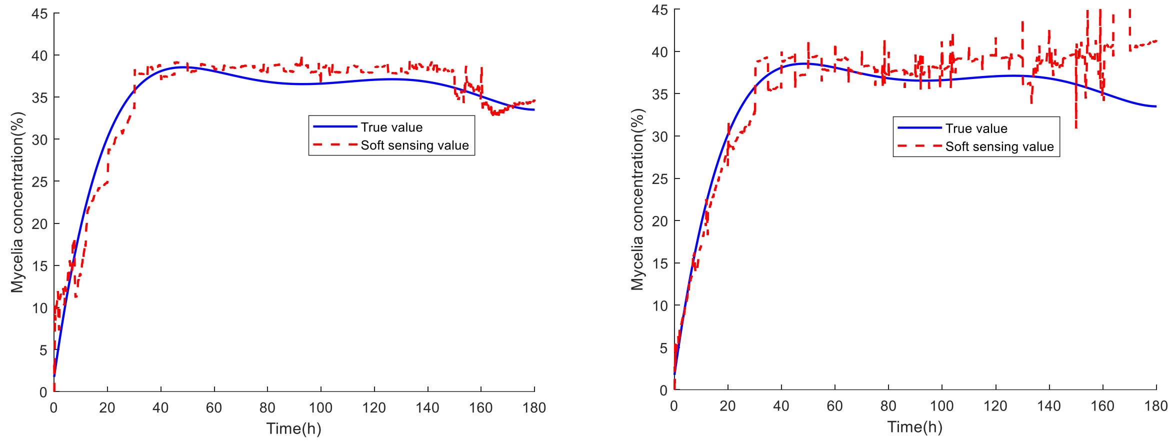
Use MIV method based on the trained neural network to calculate the contribution rate. Through the above steps the optimal input variables can be obtained, namely $C_L, pH, V_c, V_y, V_p, V_w, V_{nh}, V, \dot{C}_L, p\dot{H}, \dot{V}_c, \dot{V}_y, \dot{V}_p$. Take these variables to establish the soft sensing model for mycelia concentration X, sugar concentration S and chemical potency P as follows:

$$\begin{cases} \hat{X}=\varphi_4(C_L, pH, V_c, V_y, V_p, V_w, V_{nh}, V, \dot{C}_L, p\dot{H}, \dot{V}_c, \dot{V}_y, \dot{V}_p) \\ \hat{S}=\varphi_5(C_L, pH, V_c, V_y, V_p, V_w, V_{nh}, V, \dot{C}_L, p\dot{H}, \dot{V}_c, \dot{V}_y, \dot{V}_p) \\ \hat{p}=\varphi_6(C_L, pH, V_c, V_y, V_p, V_w, V_{nh}, V, \dot{C}_L, p\dot{H}, \dot{V}_c, \dot{V}_y, \dot{V}_p) \end{cases} \tag{9}$$

MIV method filters out the unimportant input variables, then establishes the corresponding neural network soft sensing model and test the model with the validation samples. The test results through the method are shown in Figure 1 (a), 2 (a) and 3 (a). For comparison, the test results without MIV method are shown in Figure 1 (b), 2 (b) and 3 (b). It can be seen from the graph that both the soft sensing models can obtain applicable results while the soft sensing performance of MIV method is better.

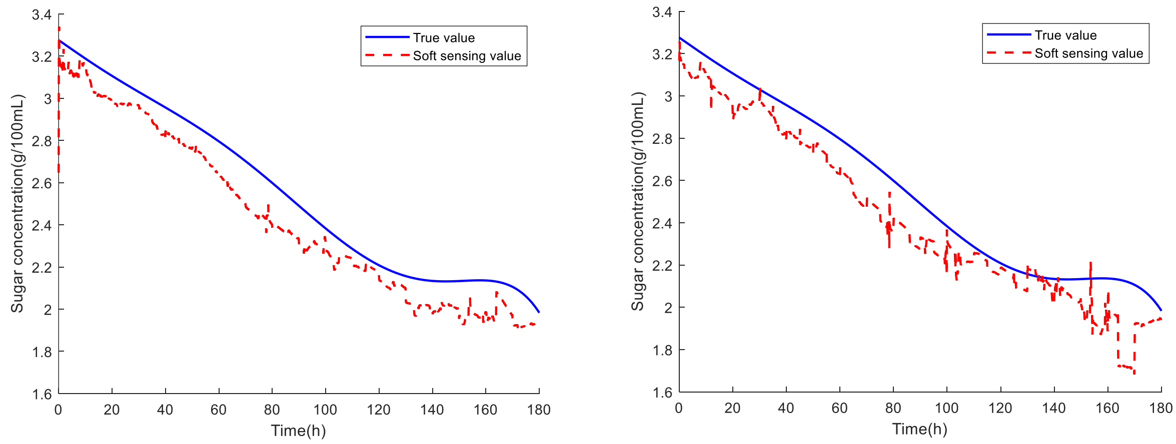
4. Conclusion

In this paper, we propose a new MIV variable selection strategy for establish an optimized soft sensing model. This method takes into account of the external contribution rate of input variables in constructing a soft sensing model. Through this method, the best input variables can be sorted out, which effectively overcomes the unsteadiness of contribution rate in traditional selection methods, and therefore provides a powerful selection method for soft sensing technology. Through soft sensing experiment of key variables in the erythromycin fermentation process, it is indicated that the MIV based variable selection method simplifies the soft sensing model and improves the estimation accuracy.



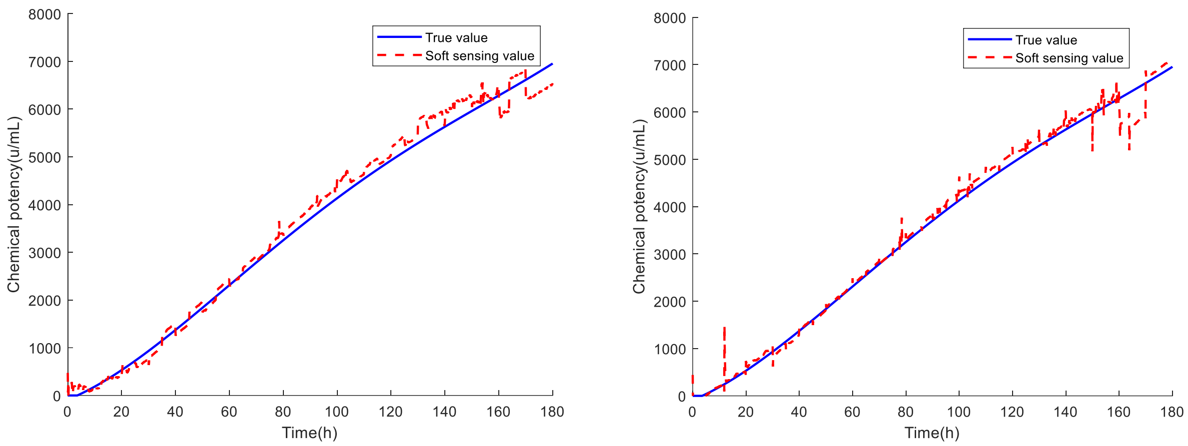
(a) Result with MIV (b) Result without MIV

Figure 1. Soft sensing results of mycelia concentration (X)



(a) Result with MIV (b) Result without MIV

Figure 2. Soft sensing results of sugar concentration (S)



(a) Result with MIV (b) Result without MIV

Figure 3. Soft sensing results of chemical potency (P)

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