A FAULT DIAGNOSIS METHOD FOR FERMENTATION PROCESS

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Abstract: Process fault diagnosis requires the on-line information on process state variables that are often inaccessible in real-time for the processes like a fermentation process. A composite model is proposed, combining a kinetic model of the first principles and a neural network model that models the kinetic model parameters changes, to estimate on line the states. This composite model can retain and enhance the process knowledge, at the same time, avoid the complexity of modeling the entire process by kinetics. The estimated process states from the composite model are then fed to a wavelet network for fault detection and diagnosis. The proposed system is successfully applied to a glutamic acid fermentation process, demonstrating the feasibility and effectiveness of the proposed system.

Keywords: fault diagnosis, RBF neural network, wavelet network, parameters estimation, ferment process

1. INTRODUCTION

Fault detection and diagnosis have become important tools to ensure quality, safety, and efficiency for many process industries. The detection and diagnosis reply on the analysis and identification of differences of features (or patterns) of the process, reflected by the process states. Measurement of proper process status, typically represented by as the process states, is a prerequisite for the success of a proper fault detection and diagnosis. For a fermentation process, however, there lacks proper sensors for on-line real-time measurement of key state variables. In such cases, methods have to be developed to estimate key process states for process diagnosis.

Generally, two types of models have been developed for state estimation: first-principle based model and black-box based model such as a neural network. For fermentation process, many kinetic models have been developed, based on the principles of physics, chemistry, and biology, to reflect the generation and growing courses of the process (Liu et al., 1997). One of challenge in this type of models is to obtain proper parameters used in the model, many of which are in fact changing with time and process conditions. For example, in the growing stage of a fermentation process, process perturbations can lead to significant changes in the kinetic model parameters. However, modeling of these changes in the model parameters can be a challenging task. For this reason, model parameters are often assumed to be “constants” in many cases. This, obviously, can result in deviations of the estimated states from their true values, leading to improper diagnosis. The black-box modeling approach can map an input-output relation, without using any process knowledge. Neural networks are often used to model this input-output type of black-box relations (Zhao et al., 1999; Maki et al., 1997). Artificial neural networks (ANNs) have also been used for fault diagnosis for fermentation process (Zhang et al., 2001; Wang et al., 1997; Abhinandan et al., 2002). A black-box model relies on process input-output information only; this type of models typically can not be extended beyond to the cases where the operating conditions are not covered by the training data. Compared to a kinetic model, a black-box model can only promote limited enhancement of process knowledge.

This paper proposes a composite modeling strategy that combines a kinetic model with a neural network model to estimate on-line process states, the estimated states are fed to a wavelet network for fault detection and diagnosis. The kinetic model used can represent the true process mechanism, retaining and enhancing the process knowledge. While the complex modeling of the changes of the kinetic model parameters with the process conditions is carried with an RBF neural network. The wavelet network is developed to analyze and recognize fault patterns, based on on-line estimation of the process states from the composite model. Finally, the proposed system, consisting of the composite model for the state estimation and the wavelet network for the diagnosis, is applied to a glutamic acid fermentation process, to demonstrate the effectiveness of the proposed method.

2. THE DESIGN OF COMPOSITE MODEL

To illustrate the method proposed in this work, a fermentation process is used with the following kinetic model.

$$\frac{dx_1}{dt} = \mu x_1 + K_1$$
$$\frac{dx_2}{dt} = b x_1 \frac{x_3}{K_s + x_3}$$
$$\frac{dx_3}{dt} = -\frac{1}{Y_G}\mu_m x_1 (1 - \frac{x_1}{x_m}) - \frac{1}{Y_p} b x_1 \frac{x_3}{K_s + x_3} - m x_1 \tag{1}$$

where $x_1(t)$, $x_2(t)$, and $x_3(t)$, representing the concentrations of biomass, substrate, product respectively, can not be measured on-line for process diagnosis. μ is the growth rate of biomass, x_m is the maximum biomass concentration, b is the maximum production rate of the acid, K_s is the saturation constant of substrate, Y_G is the yield coefficient of biomass, Y_p is the yield coefficient of product, m is the maintenance coefficient of the biomass. Y_p and μ change with the degree and the conditions of the fermentation of the process.

Fermentation is a complex process, any contamination, improper medium formulation, and improper addition of the trace element can upset the normal production, leading to process faults. In correspondence, the process states, which are represented by the concentrations of biomass, substrate, product, will change differently from a normal product to reflect the process abnormality. The kinetic model parameters, such as Y_p and μ, will change as well. To predict process states correctly, these kinetic model parameters need to be updated. It is a very complex task to model the changes of the kinetic parameters, based on the first-principles. A RBF neural network is proposed to correlate the parameter changes with the process conditions, resulting in a composite model for the state estimation. The over-all scheme for the fermentation process diagnosis is illustrated as Figure 1.

Although the kinetic parameters Y_p and μ can not be measured directly either, they may be related to some measurable process variables, such as pH, dissolved oxygen (DO), and temperature (T). In other words, these kinetic parameters may be predicted from these directly measurable variables, if their relations to these variables can be established. Using the history data collected off-line, this kind of relations may be modelled via a neural network between the measurable variables and the kinetic parameters assayed. The neural network can be used online to estimate the kinetic parameters, after it is well-trained offline.

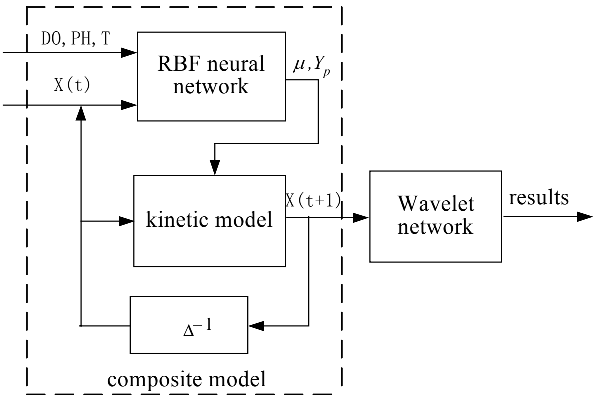


Fig. 1 Schematic of fault diagnosis strategy

Radial basis function (RBF) network, a feed forward network, is adopted for such a propose, as it has good ability of approximation and modeling (Wang , 1997; Chen, 1991). A nonlinear mapping can be realized between the input and the output of a nonlinear process as following:

$$f(X) = W_0 + \sum_{i=1}^{n} W_i * \phi(\| X - c_i \|) \tag{2}$$

where $X \in R^n$ is the vector of input, $\phi(\cdot)$ is radial basis function of $R^+ \to R$, W_i is the weights of network, c_i is the center of data, and n is the number of the center. We choose $\phi(\cdot)$ as Gauss function. Here, RBF is used to supply the estimated values of kinetic parameters for the kinetic model.

The RBF network is trained with history data consisting of pH, DO, T, the assayed values, etc. After the training, the mapping relationship has built. The composite model, composing of the trained RBF network for estimating the kinetic parameter changes and the kinetic model for estimating the states, can be used to provide state information on-line to the wavelet network for fault diagnosis as described below.

3. FAULT DIAGNOSIS

Wavelet analysis has found many applications, due its strength in analyzing transient behaviours and signal compression. It is selected here to recognize the patterns of the faults associated with the fermentation process. An evolving wavelet network (Huang et al., 2002) is chosen to capture the relationships of process states to the corresponding fault types.

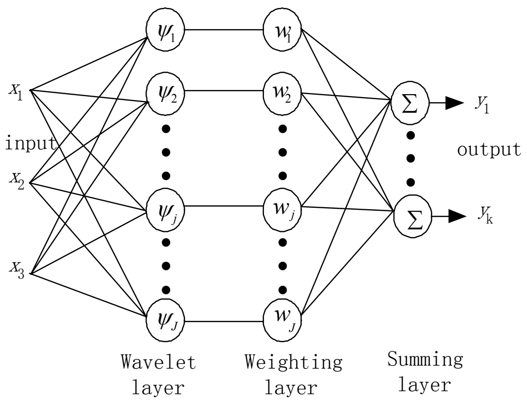


Fig. 2 Wavelet networks

The proposed wavelet networks for the fault diagnosis has a three-layer structure with a wavelet layer (input layer), weighting layer (intermediate layer), and summing layer (output layer). Each layer has one or more nodes. Figure 2 gives a schematic representation of the three-layer wavelet networks. The input data vector x, as shown in Figure 2, is the input nodes of the networks, expressed as:

$$x = [x_1, x_2, \cdots x_n]^T \ , \tag{3}$$

where the input variables are the outputs of the composite model designed above. The activation functions of the wavelet nodes in the wavelet layer are derived from a mother wavelet $\psi(x)$. Then, the function of $\psi(x)$ can become the mother wavelet with dilation of d and translation of t

$$\psi_{d,t}(x) = 2^{d/2}\psi\,(2^d x - t)\,, \qquad d, t \in Z \tag{4}$$

where Z indicates the integers. Via the operation of dilation and translation, the wavelets of (4) possess superior localization performance in both time and frequency. Since the Laplacian of the Gaussian function family meets the isotropic admissibility condition, the function of $\psi(x) = -xe^{-(1/2)x^2}$ is selected as the mother wavelet herein. Therefore, the activation function of the jth wavelet node $j = 1, 2, \cdots, J$ has the following form:

$$\psi_{d_j, t_j}(x) = -2^{d_j/2}\,(2^{d_j} x - t_j)\, e^{-0.5(2^{d_j} x - t_j)^2} \qquad d_j \;\; t_j \in Z \tag{5}$$

Each output of the weighting nodes in the weighting layer is multiplied by an appropriate weight value determined by the weighting node. In Figure 2, the weights w_{jk}, that connect the jth weighting node and the kth output node, are indicated by the weighting vectors $w_j = [w_{j1}, w_{j2}, \cdots, w_{jk}, \cdots w_{jK}]$ for $j = 1, 2 \cdots, J$ and $k = 1,2,\cdots, K$, and K is the number of the output nodes. The weighted sum of the output of J weighting nodes in the weighting layer produces the final output of the summing layer

$$y_k(x) = \sum_{j=1}^{J} w_{jk}\psi_j(x) \tag{6}$$

where $y_k(x)$ is the kth final computed output value of the networks. Note that the output $y_k(x)$ in (6) contains, implicitly, the adjustable parameters of the networks: the connection weights (w_{jk}) and the parameters, dilation (d_j), and translation (t_j) in each wavelet node.

The training algorithm for the wavelet network is as follows. The assayed data with the normal as well fault process operations are presented as the training data to the network as described above. Any output of value 1 indicates the occurrence of the fault specified by its fault type. The wavelet parameters of dilation, translation, and weighting values of the networks are determined by the evolutionary algorithm of Fogel (1994), a global-optimal approach.

4. APPLICATION EXAMPLE

The proposed diagnosis system consisting of a wavelet network for diagnosis and a composite model of on-line state estimation is put into tests with a glutamic acid fermentation process (Zhao, et al., 1999). The kinetic model of the process is described as Equation (1), where the process states of $x_1(t)$, $x_2(t)$, and $x_3(t)$ are concentrations (g / l) of biomass, glutamic acid, and glucose, respectively. They can not be measured on-line in real-time. $\mu = \mu_m x_1(1 - x_1 / x_m)$, here, $\mu_m = 0.767\ h^{-1}$ is the maximum specific growth rate, $x_m = 6.43\ (g/l)$ is the maximum biomass concentration. $b = 0.358\ h^{-1}$, $K_s = 12.04\ (g/l)$, $Y_G = 0.436$, $Y_P = 0.645$, and $m = 0.105\ h^{-1}$.

The sampling time is 45 minutes. The designed RBF network has the structure of 6-4-2. The wavelet network has three inputs and six outputs describing different process operation status (faults), the details of the wavelet outputs are described in Table 1. These outputs indicate the different fault types of the process. During the operation, any output besides y1 with a value greater than 0.5, the corresponding process fault is assumed to have occurred.

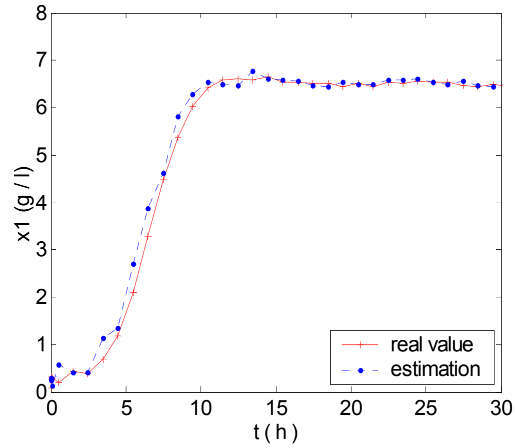
Table 1 Definition of the output of wavelet network

output	Fault type
y1	normal
y2	poor growth
y3	thallus degradation
y4	abnormal consumption of substrate
y5	concentration abnormity
y6	contamination

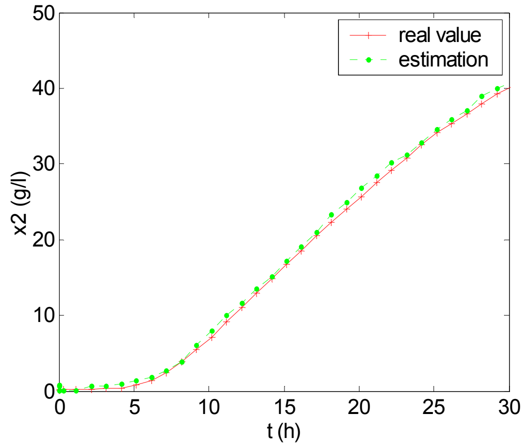
The system is put into tests with a normal process operation. Figure 3 compares the estimates of the states by the composite model with the actual values obtained from the assayed data. Figure 4 is another comparison of the process states obtained by the on-line composite model with the assayed data for a poor growth operation case. In both cases, the on-line composite model can estimate the state variables well, demonstrating the application potentials of the proposed composite state estimation scheme. The fault diagnosis ability of the proposed system is also tested with these two cases. For the normal operation, the only output with a value greater than 0.5 is y1, indicating a normal operation. For the poor growth case, the only wavelet output with a value greater than 0.5 is y2, indicate the correct fault type. The time variations of the two operation cases are plotted in a single graph as Figure 5, to save the space. A comparison of the diagnoses of these two cases indicates that the proposed system can detect and make a proper diagnosis of the faults in the fermentation process.

5 CONCLUTION

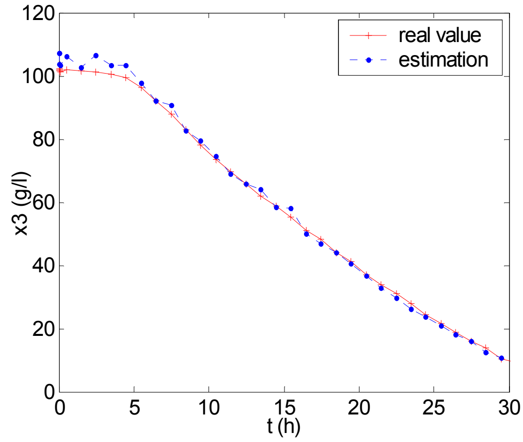
A composite model combining of a neural-network model and a kinetic model has been proposed to provide on-line estimation of process states. Based on the estimation of the process states, a wavelet model has been developed for process fault detection and diagnosis. The use of the proposed composite models can avoid the complexity introduced by building a pure kinetic model for the process. At the same time, unlike a black-box model, the proposed composite model can retain the key process features as reflected by the process kinetics, this can enhance process understanding. The estimates of the process states from the composite model are fed to a wavelet network for process fault detection and diagnosis. This allows an on-line diagnosis possible, without the need of measuring on-line inaccessible state variables. The applications of the proposed system to a glutamic acid fermentation process indicate that the system can successfully recognize and discriminate faults of the process.



a) concentrations of biomass

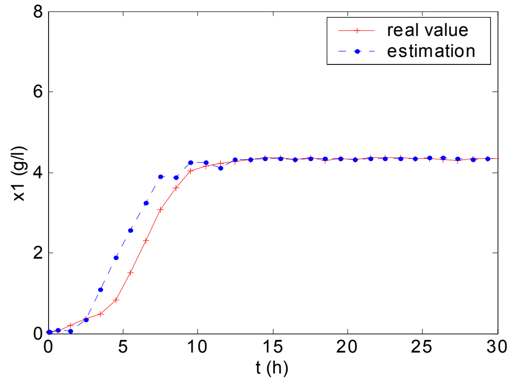


b) concentrations of glutamic acid

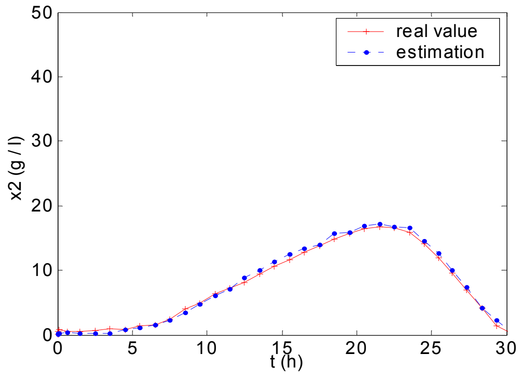


c) concentrations of glucose

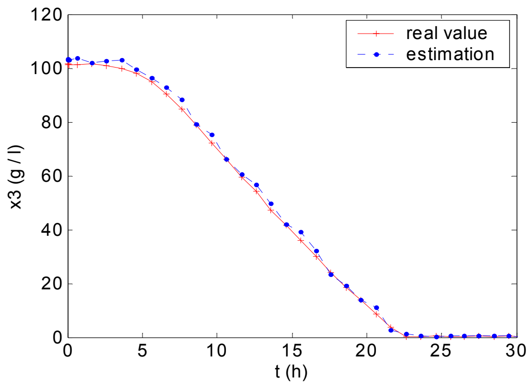
Fig. 3. Comparison of state estimates and assayed values for a normal operation.



a) concentrations of biomass



b) concentrations of glutamic acid



c) concentrations of glucose

Fig. 4. Comparison of state estimates with the assayed values for a faulty operation.

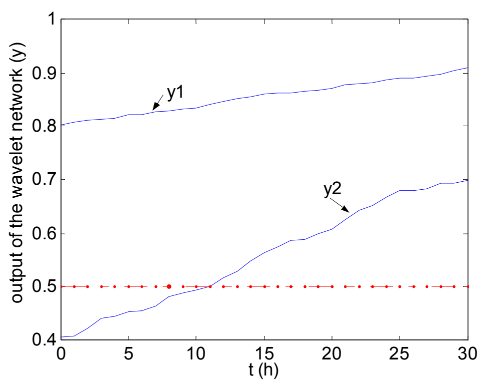


Fig. 5. The output of the diagnosis wavelet network for a normal operation (y1) and a faulty operation (y2).

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