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NEURAL NETWORK DYNAMIC IDENTIFICATION OF A FERMENTATION PROCESS

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ABSTRACT

System identification is a major component for a control system. In biosystems, which is nonlinear and dynamic, precise identification would be very helpful for implementing a control system. It is difficult to precisely identify such nonlinear systems. The measurable data on products from 2,3-butanediol fermentation could not be included in a process model based on kinetic approach. Meanwhile, a predictive capability is required in developing a control system. A neural network (NN) dynamic identifier with a bt/(1+|t|) transfer function was therefore designed being able to predict this fermentation. This modified inverse NN identifier differs from traditional models in which it is not only able to see but also able to predict the system. A moving window, with a dimension of 11 and a fixed data size of seven, was properly designed. One-step ahead identification/prediction by an 11-3-1 BPNN is demonstrated. Even under process fault, this neural network is still able to perform several-step ahead prediction.

1. Introduction

The purpose of system identification is to search for a process model which relates outputs of a system to control input command. System identification is one type of model such that the information from this model should be referred to control command and be able to provide a better foundation for control.

Product distribution of 2,3-butanediol (2,3-BDL) fermentation could be governed by oxygen supply. 2,3-BDL is produced at an optimal fractional yield under a partially anaerobic condition [1]. We would therefore prefer to relate the information on products to the information on oxygen supply. Oxygen availability to cells depends upon dissolved oxygen (DO) and oxygen uptake rate (OUR). The DO value, in turn, could be regulated by oxygen partial pressure (or oxygen composition) in the gas phase. Oxygen composition is thus used as the control input parameter. The data on products would thus be needed for identifying the fermentation. Four products, acetic acid, acetoin, ethanol, and 2,3-BDL, were all measured.

The ability of identifying bioprocesses by neural network (NN) has been demonstrated [2]. Accordingly, neural network for system identification would be tested from this complicated fermentation. Predictive capability is an important component for a control system. Therefore, we would design the identification with prediction function.

A fermentation process is usually a nonlinear, time-variant system. It is a system with slow reaction so the sampling interval could be allowed minutes. The whole range for product concentrations during a fermentation varies a lot. It is rather difficult to find a proper model for identifying the whole course of a fermentation. Most process models with fixed parameters are from kinetic approach which usually could not well identify such dynamic fermentation processes. Therefore, instead of a static kinetic model, the identification from dynamic approach with adaptively adjusted pa-

rameters would be searched.

A precise process model and a good controller model are essential to a control system.

The process model (identification) can be expressed as:

$$x_i = f(u_i) \qquad (1)$$

where x_i is the monitored outcome (at time i) from the system, and u_i is the control command (w.r.t. x_i) to the system.

The controller model can be expressed as:

$$u'_{i+1} = g(\mathbf{x}_i, \mathbf{u}_i, x_{i+1}^d) \qquad (2)$$

where u'_{i+1} is the predicted control command w.r.t. x_{i+1}^d, the desired x for next measurement (at time i+1);

$\mathbf{x}_i = (x_0, ..., x_{i-1}, x_i)$, the array of measured data up to time i;

$\mathbf{u}_i=(u_0,...,u_i)$, the array of corresponding control commands;

Equations (1) and (2) are inverse to each other. These two equations must be coupled together to complete a control system. Therefore, Equation (1) must be converted to get the expression on $\mathbf{u}_i$, i.e., $\mathbf{u}_i = \mathbf{f}_i^{-1}$.

The result is then merged into Equation (2):

$$u'_{i+1} = g(\mathbf{x}_i, \mathbf{f}_i^{-1}, x_{i+1}^d) \qquad (3)$$

where $\mathbf{f}_i^{-1} = (f^{-1}(x_0), ..., f^{-1}(x_{i+1}), f^{-1}(x_i))$

The equation for process model must be inversible, in other words, for the function, $f(\cdot)$, there must exist $f^{-1}(\cdot)$ (a one on one mapping between $f(\cdot)$ and $f^{-1}(\cdot)$). If $f(\cdot)$ is not inversible, for a particular x, there might exist more than one u, which would lead to an unstable control.

2. System Description

2.1 Modified Inverse-type Neural Network Identification

For avoiding the inversion of process model, an inverse-type process model was implemented [3] to control a time-invariant nonlinear system with unknown dynamics.

$$u_i = f(x_i) \qquad (4)$$

Accordingly, we therefore consider, in a similar way, to design an inverse-type model for this fermentation, however, with modification. The identification will be so constructed that all the measured product concentrations relate to the oxygen composition. Neural network (NN), with the powerful identification capability, will be used for this modified inverse process model. Prediction performed by NN has been demonstrated [4,5]. Prediction capability is important for control. As a result, the identification will be designed being able to predict.the future control command. This has never been done with conventional and any other existing process models. In addition, NN identification is of a modified inverse type so that the past information on products and oxygen composition is also included, which is different from conventional approach and the inverse-type model, i.e.,

$$u_i = f(\mathbf{x}_i, \mathbf{u}_{i-1}) \qquad (5)$$

Such a design of process identification would benefit followed control. Once given a desired output, the control command w.r.t. this desired output could be computed in a straightforward manner. More precisely, the process model and the controller model from such design are in the same form but differ only by providing measured output to this process model and desired output to switch to a controller model.

$$u'_{i+1} = f(\mathbf{x}_i, x_{i+1}^d, \mathbf{u}_i) \qquad (6)$$

The NN identification/prediction for this fermentation is thus tested and could be expressed as follows:

$$u(i+1) = f(u(i-1), u(i), \mathbf{P}(i-1), \mathbf{P}(i), P_4(i+1)) \qquad (7)$$

where u(i+1) is the predicted oxygen composition w.r.t. the measured data at time i+1. u(i-1) and u(i) are the O_2 composition fed to the system at time i-1 and i, respectively. $\mathbf{P}(i) = (P_j(i))$, the array of four product concentrations measured at time i and j=1, 2, 3, 4, for acetic acid, acetoin, ethanol, and 2,3-BDL, respectively. $\mathbf{P}(i-1)$ is defined as the array of measurements at time i-1 accordingly. $P_4(i+1)$ is the 2,3-BDL concentration measured at time i+1, which, in turn, is switched to the desired 2,3-BDL concentration for the controller model while this formula is alternated.

2.2 Fermentation System

A 2L fermentor has a motor/controller to control the agitation speed at 600 rpm. Temperature was controlled at 37°C. pH was detected and controlled at 5.7. Air was supplied to the fermentor through a filter disk.

A gas mixer was constructed for control of inlet gas flow rate and composition by the mixing of N_2 and air. The main components are two mass flow controllers. Each receives

0 to 5V signals which produce corresponding flow rates of 0 - 4/3v/v/m. Gas flow rate could be varied by supplying varying voltages to each mass flow controller. The oxygen composition was controlled by a D/A board, DDA-06 unit. The output range was from 0 to +10 V which is the full input range for N_2 and air two ports. DDA-06 must be calibrated with supplied calibration/installation program before use.

3. Results and Discussion

Fig. 1 shows the plot of four products, acetic acid, acetoin, ethanol, and 2,3-BDL, measured from a batch fermentation. The fermentation is to produce the major product, 2,3-BDL, as a secondary metabolite. Cell growth and product distribution are governed by air supply. A sufficient air supply directs the pathway to grow cells while an intermediate air supply favors 2,3-BDL production. Aeration is obviously very important to cell growth. This fermentation was therefore divided into two phases, during the first phase, air was sufficiently supplied to grow cells, while during the second phase, the aeration was decreased to stimulate the production of 2,3-BDL. Therefore, the schedule on O_2 supply was designed according to the above considerations.

3.1 Neural Network Identification/Prediction

3.1.1 Without Process Fault

Neural network identification/prediction was carried out by providing fermentation data generated from predetermined O_2 input schedule. Factors such as number of inputs (i.e., dimension of the moving window), number of outputs, number of neurons in hidden layer, number of data sets for learning were all tested. A transfer function of the saturation form, bt/(1+|t|) [2,4], was successfully implemented.

An 11-3-1 BPNN with seven learning data sets, as shown in Fig. 2, was found from this effort. The 11 inputs include the four product concentrations measured at time i-1 and i, the oxygen composition provided to the system at time i-1 and i, and the 2,3-BDL concentration measured at time i+1. The output is the predicted (or provided) oxygen composition at time i+1. The input/output data for learning can be written as $\{(\mathbf{P}(i-1),u(i-1),\mathbf{P}(i),u(i),P_4(i+1)):u(i+1)|i=1, 2, 3, ..., 7\}$.

In the first seven learnings, data file was expanding while newly measured data was added along the time course. Starting from the eighth learning, the first data set was excluded while a new measurement was added. The size of data file for an usual moving window is one while a size of seven was found optimal for this window. From this moving window of seven data sets, the dynamic NN identification/prediction was thus built. It is not only able to identify this process, but also able to work out one-step ahead prediction. The result on identification/one-step ahead prediction performed by this 11-3-1 BPNN is shown in Fig. 3. Errors (could be resulted from the measurement and the computation) are plotted in Fig. 4.

3.1.2 With Process Fault

The process was interrupted by fault in several batches. If the measured data is not obtained, could it be possible to search for such an identifier with the ability to see several-step ahead? The unavailable measurements could thus be ignored. How this identification/prediction performs with process fault was therefore examined. Fig. 5 shows the identification/prediction results of this 11-3-1 BPNN with interrupted measurements. The measurement was interrupted for more than one hour. Predicted value of the O_2 composition right after this one-hour interruption was reasonable. There are at least 9 measurements in each hour, the success of the work indicates that this identification could perform the prediction up to 9-step ahead. The average relative error, with limited computation time of 40 seconds, for each prediction is shown in Fig. 6. The learning time was limited so that the further on-line control system could be possibly accommodated.

4. Conclusion

The dynamic identification/prediction of 2,3-BDL fermentation was successfully performed by a 11-3-1 BPNN. A transfer function, bt/(1+|t|), with BPNN has demonstrated its ability in identifying nonlinear systems. This identification was prepared such that the inversion of process model could be avoided. This dynamic identification differs from traditional process models in which it has prediction capability.

One-step ahead prediction and even several-step ahead prediction were both performed from such neural network identification. A moving window with dimension of 11 (i.e., the number of inputs in this BPNN identifier) to view seven data sets for each learning was successfully implemented. In case of process fault, or if the on-line monitoring system was interrupted, this 11-3-1 BPNN could still provide available information to the process by several-step ahead prediction. The success of this modified inverse type identification should benefit the future control system. This identification was prepared such that the inversion of process model could be avoided.

5. References

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Fig. 1 Product concentrations of 2,3-BDL fermentation with a predetermined oxygen schedule

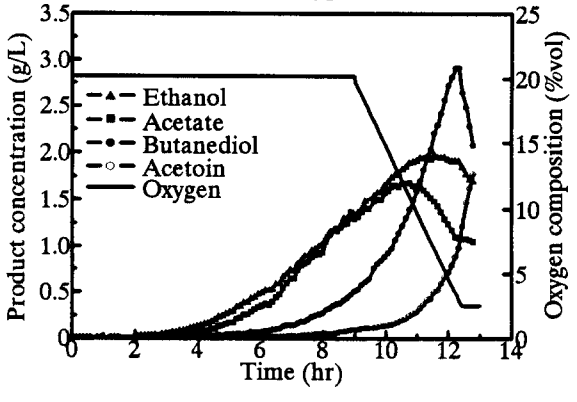

Fig. 2 11-3-1 Back-propagation neural network for dynamic identification/prediction

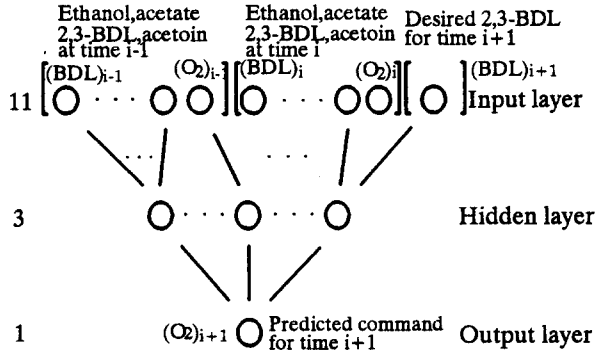

Fig. 3 One-step ahead prediction of O_2 by an 11-3-1 BPNN.

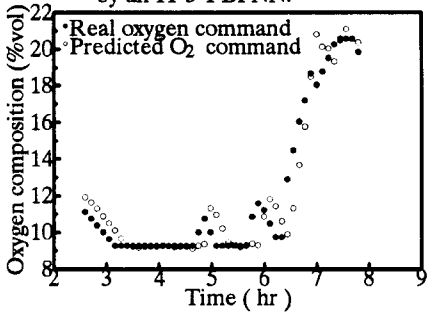

Fig.4a Computation time for each identification

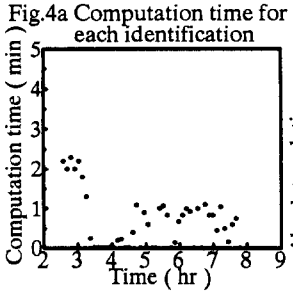

Fig.4b Average relative error for each identification

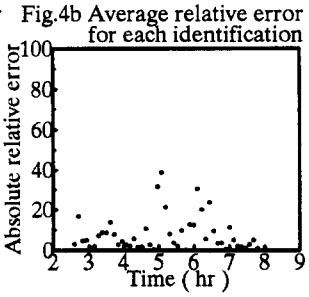

Fig. 5 Few-step ahead prediction of O_2 by an 11-3-1 BPNN identification

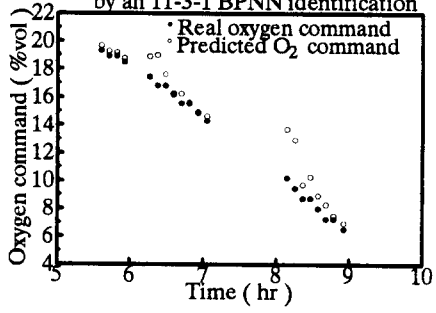

Fig. 6 Average relative error with limited computation time