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Multivariable decoupling control based on fuzzy-neural network αth-order inverse system in fermentation process

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Abstract: This paper proposes a nonlinear multivariable decoupling control strategy based on fuzzy-neural network αth-order inverse method that combines inverse system theory with fuzzy-neural network for fermentation process. A nonlinear inverse model is developed based on the reversibility analysis of the process model. A fuzzy-neural network αth-order inverse system is then constructed, which is cascaded with this process to transform the original nonlinear system to a pseudo-linear system. Finally, an expert controller is used to closed-loop synthesis. The effectiveness of the presented method is illustrated by a simulation experiment.

Key words: bioprocesses; fuzzy-neural network; inverse system method; decoupling control; expert controller

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基于模糊神经网络α阶逆系统的发酵过程多变量解耦控制

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摘要: 将逆系统方法与模糊神经网络相结合, 提出一种基于模糊神经网络α阶逆系统的发酵过程解耦控制方法. 在分析了系统可逆性的基础上, 利用模糊神经网络建立发酵过程的非线性逆模型, 然后将得到的模糊神经α阶逆系统与发酵过程串联复合成伪线性系统, 最后设计专家控制器实现高性能闭环解耦控制. 仿真结果表明, 提出的解耦控制方法能够适应发酵过程模型的不确定性和参数的时变性, 具有较强的鲁棒性, 克服了解析逆系统解耦控制方法依赖于过程模型和对模型参数的变化很敏感的缺点, 且结构简单, 易于实现.

关键词: 生化反应过程; 模糊神经网络; 逆系统方法; 解耦控制; 专家控制器

1 Introduction

Bioprocess is a nonlinear multivariable coupling system for involving complex factors such as microbial cells growth, metabolism and so on[1]. Decoupling control of this nonlinear multivariable system is a research topic of both theoretical and practical importance. Among these nonlinear system theories, the inverse system method is verified to be powerful[2,3]. Unfortunately, this method is based on an exact mathematical model of the plant, which is impossible to obtain in bioprocess. To adopt the inverse system method in bioprocess, it is required to identify the structure of the αth-order inverse system without exact knowledge of mathematical model of the system model[4,5]. Among these identification methods, fuzzy-neural network, which possesses merits of both fuzzy logic and neural network, has proved to be more powerful and has been widely used in practical engineering[6,7].

This paper presents a multivariable decoupling control method based on fuzzy-neural network αth-order inverse system for fermentation process. Through analyzing the reversibility of the system model, a fuzzy-neural network αth-order inverse system is built, which is placed in series with the original fermentation system to transform it to three pseudo-linear composite subsystems. Finally, an expert PID controller strategy is given for closed-loop synthesis. An experiment is preformed to verify the effectiveness of our method.

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2 Mathematical model and reversibility analysis

The mathematical model of the fermentation process can be described as[1]

$$\begin{cases} \dfrac{\mathrm{d}X}{\mathrm{d}t} = \varphi X - \dfrac{X}{V}\dfrac{\mathrm{d}V}{\mathrm{d}t}, \\ \dfrac{\mathrm{d}S}{\mathrm{d}t} = \phi X + \dfrac{k_1}{V} f_{\mathrm{c}} - \dfrac{S}{V}\dfrac{\mathrm{d}V}{\mathrm{d}t}, \\ \dfrac{\mathrm{d}P}{\mathrm{d}t} = \sigma X - k_2 p + \dfrac{k_3}{V} f_{\mathrm{n}} - \dfrac{P}{V}\dfrac{\mathrm{d}V}{\mathrm{d}t}, \\ \dfrac{\mathrm{d}V}{\mathrm{d}t} = f_{\mathrm{ph}} + f_{\mathrm{c}} + f_{\mathrm{n}}, \end{cases} \tag{1}$$

where: X, S and P are mycelia concentration, substrate concentration and chemical potency [g/L], V is the volume of cultivation broth in bioreactor [L], f_{ph}, f_{c} and f_{n} are the flow rate of ammonia, glucose and nitrogen source, respectively [l/h], t is time [h]; $k_i \neq 0$ $(i = 1, 2, 3)$ are constant scalars, φ, ϕ, σ are analytic functions of state variables.

Let $\boldsymbol{x} = (x_1, x_2, x_3, x_4)^{\mathrm{T}} = (X, S, P, V)^{\mathrm{T}}$ be state vector, $\boldsymbol{u} = (u_1, u_2, u_3)^{\mathrm{T}} = (f_{\mathrm{ph}}, f_{\mathrm{c}}, f_{\mathrm{n}})^{\mathrm{T}}$ be input vector. Then system (1) can be rewritten in the following state-space form:

$$\begin{cases} \dot{x}_1 = \varphi x_1 - \dfrac{x_1}{x_4}(u_1 + u_2 + u_3), \\ \dot{x}_2 = \phi x_1 + \dfrac{k_1}{x_4} u_2 - \dfrac{x_2}{x_4}(u_1 + u_2 + u_3), \\ \dot{x}_3 = \sigma x_1 - k_2 x_3 + \dfrac{k_3}{x_4} u_3 - \dfrac{x_3}{x_4}(u_1 + u_2 + u_3), \\ \dot{x}_4 = u_1 + u_2 + u_3. \end{cases} \tag{2}$$

The output vector is

$$\boldsymbol{y} = (y_1, y_2, y_3)^{\mathrm{T}} = (x_1, x_2, x_3)^{\mathrm{T}}. \tag{3}$$

To use fuzzy-neural network αth-order inverse system method, the reversibility of this system should be verified first. The integrity mathematical description of this system is

$$\begin{cases} \boldsymbol{y} = (y_1, y_2, y_3)^{\mathrm{T}} = (x_1, x_2, x_3)^{\mathrm{T}}, \\ \dot{x}_4 = u_1 + u_2 + u_3. \end{cases} \tag{4}$$

Direct computation gives the following expression for $\dot{\boldsymbol{y}}$:

$$\dot{\boldsymbol{y}} = \begin{bmatrix} \phi y_1 - \dfrac{y_1}{x_4}(u_1 + u_2 + u_3) \\ \varphi y_1 + \dfrac{k_1}{x_4} u_1 - \dfrac{y_2}{x_4}(u_1 + u_2 + u_3) \\ \sigma y_1 - k_2 y_3 + \dfrac{k_3}{x_4} - \dfrac{y_3}{x_4}(u_1 + u_2 + u_3) \end{bmatrix}, \tag{5}$$

which explicitly contains $\boldsymbol{u}$, and the rank of Jacobean matrix is

$$\mathrm{rank}[\frac{\partial \dot{\boldsymbol{y}}}{\partial \boldsymbol{u}^{\mathrm{T}}}] = \mathrm{rank}\begin{bmatrix} \dfrac{\partial \dot{y}_1}{\partial u_1} & \dfrac{\partial \dot{y}_1}{\partial u_2} & \dfrac{\partial \dot{y}_1}{\partial u_3} \\ \dfrac{\partial \dot{y}_2}{\partial u_1} & \dfrac{\partial \dot{y}_2}{\partial u_2} & \dfrac{\partial \dot{y}_2}{\partial u_3} \\ \dfrac{\partial \dot{y}_3}{\partial u_1} & \dfrac{\partial \dot{y}_3}{\partial u_2} & \dfrac{\partial \dot{y}_3}{\partial u_3} \end{bmatrix} =$$

$$\mathrm{rank}\begin{bmatrix} -\dfrac{x_1}{x_4} & -\dfrac{x_1}{x_4} & \dfrac{x_1}{x_4} \\ \dfrac{k_1 - x_2}{x_4} & -\dfrac{x_2}{x_4} & -\dfrac{x_2}{x_4} \\ -\dfrac{x_3}{x_4} & -\dfrac{k_3 - x_3}{x_4} & -\dfrac{x_3}{x_4} \end{bmatrix} =$$

$$\mathrm{rank}\begin{bmatrix} 1 & 1 & 1 \\ k_1 & 0 & 0 \\ 0 & k_3 & 0 \end{bmatrix} = 3. \tag{6}$$

In practical fermentation process, $x_i \neq 0 (i = 1, 2, 3)$, $k_i \neq 0 (i = 1, 2, 3)$ and then

$$\det[\frac{\partial \dot{\boldsymbol{y}}}{\partial \boldsymbol{u}^{\mathrm{T}}}] = -\frac{x_1}{x_4^3}\begin{bmatrix} 1 & 1 & 1 \\ k_1 & 0 & 0 \\ 0 & k_3 & 0 \end{bmatrix} = -\frac{y_1 k_1 k_3}{x_4^3} \neq 0. \tag{7}$$

The relative degree of system (4) is $\alpha = (\alpha_1, \alpha_2, \alpha_3)^{\mathrm{T}} = (1, 1, 1)^{\mathrm{T}}$ satisfying $\alpha_1 + \alpha_2 + \alpha_3 = 1 + 1 + 1 = 3 < 4 = n$, which indicates the reversibility of systems (4)(3). By implicit function existence theorem, the inverse system of system (4), (3) can be expressed by

$$\boldsymbol{u} = [u_1, u_2, u_3] = \psi(x, y_1, \dot{y}_1, y_2, \dot{y}_2, y_3, \dot{y}_3). \tag{8}$$

3 Nonlinear system identification theory and method of fuzzy-neural network

For an MISO nonlinear system $y = f(\boldsymbol{x})$ with $\boldsymbol{x} = (x_1, x_2, \cdots, x_m) \in \boldsymbol{X} \subset \mathbb{R}^n$, $y \in Y \subset \mathbb{R}$. For input-output sample data $(\boldsymbol{x}_1, y_1)$, $(\boldsymbol{x}_2, y_2) \cdots (\boldsymbol{x}_{\mathrm{n}}, y_{\mathrm{n}})$, a model of fuzzy rules can be built as[8],

$$\begin{aligned} \mathbb{R}^l :\ & \text{if } x_1 \text{ is } A_1^l \text{ and } x_2 \text{ is } A_2^l \text{ and } \cdots \text{ and } x_m \text{ is } A_m^l, \\ & \text{then, } y \text{ is } B^l,\ l = 1, 2, \cdots, W. \end{aligned} \tag{9}$$

Where: W is the number of fuzzy rules, A_i^l is the fuzzy set in the universe of x_i, $\mu_{A_i}^l(x_i)(i = 1, 2, \cdots, m)$ is the membership function of x_i, B^l is the fuzzy set in the output universe of y.

Note that nonlinear system f is expressed by W fuzzy rules with singleton, product operator and weighted average of anti-fuzzy as (9). The output y can be given as

$$y = f(x) = \frac{\sum\limits_{l=1}^{W} w_i [\prod\limits_{i=1}^{m} \exp(-(-\frac{x_i - a_i^l}{b_i^l})^2)]}{\sum\limits_{l=1}^{W} [\prod\limits_{i=1}^{m} \exp(-(-\frac{x_i - a_i^l}{b_i^l})^2)]}. \quad (10)$$

As shown in Fig. 1 is the topology structure of feedforward fuzzy-neural network, where input-output relations are as follows[9]:

Input layer: Input node is x_i , output node is $O_i^{(1)} = x_i (i = 1, 2, \cdots, m)$;

Fuzzy layer: Input nodes are $(x_i - a_{ik})$ and $b_{ik} (i = 1, 2, \cdots, m)$, output node is $O_{ik}^{(2)} = \exp(\frac{-(x_i - a_{ik})^2}{b_{ik}^2})$;

Rule layer: Input nodes are $O_{1j}^{(2)}, O_{2j}^{(2)}, \cdots, O_{mj}^{(2)} (j = 1, 2, \cdots, w)$, output node is $O_j^{(3)} = O_{1j}^{(2)} \times O_{2j}^{(2)} \times \cdots \times O_{mj}^{(2)}$;

Output layer: Input nodes are $O_i^{(2)} \times w_i (i = 1, 2, \cdots, m)$, output node is $y = O^{(4)} = \sum\limits_{i=1}^{4} O_i^{(3)} \times w_i / \sum\limits_{i=1}^{4} O_i^{(3)}$.

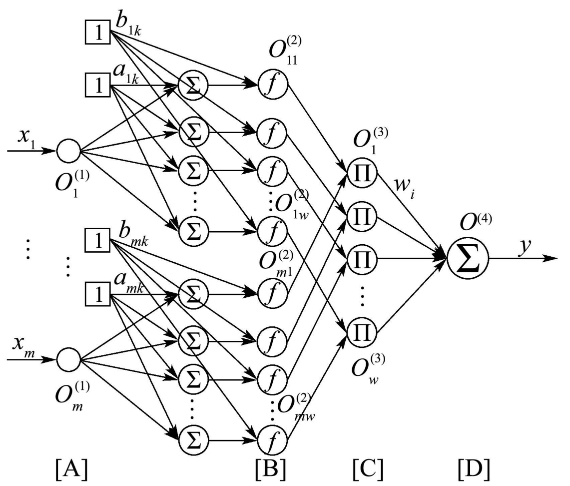


Fig. 1 Topology structure of fuzzy-neural network

For this fuzzy neural network, initial values $a_i^l(0)$, $b_i^l(0)$, $w(0)$ are determined by clustering method while the first order gradient algorithm and error back propagation method[10,11] are used to identify free parameters a_i^l, b_i^l, w_i.

4 Fuzzy-neural network αth-order inverse system decoupling control method

By the inverse system theory, the implementation of inverse system method must meet two preconditions:

1) Plant model is accurately known;

2) Analytic expression of the inverse system can be obtained from the plant model.

Unfortunately, neither of these conditions is satisfied in the actual bioprocess. Noting that fuzzy-neural network can approximate any continuous nonlinear mapping, we use it to approach the inverse system (8). With the knowledge of relative rank $\alpha = (\alpha_1, \alpha_2, \alpha_3)^{\mathrm{T}} = (1, 1, 1)^{\mathrm{T}}$, the fuzzy-neural network αth-order inverse system can be comprised with three fuzzy-neural networks and three integrators, where fuzzy-neural networks and integrators characterize the nonlinear mapping relationship and inverse system dynamics respectively. Placing this fuzzy-neural network αth-order inverse system in series with the fermentation model results in three decoupling pseudo-linear subsystems with transform functions $G_x(s) = s^{-1}$, $G_s(s) = s^{-1}$ and $G_p(s) = s^{-1}$. In this way, the complex multivariable nonlinear system (4) is compensated to three simple SISO first-order integral systems and thus expert PID controllers can be used in closed-loop synthesis.

Figure 2 shows the configuration of an expert PID controller, where the knowledge base stores specialized experiences, common sense and knowledge obtained from the fermentation expert, inference engine is essentially a set of computer programs used to coordinate the work of expert controllers. Inference engine gives the optimal controller parameters based on the current input data, knowledge base and certain reasoning strategies[12].

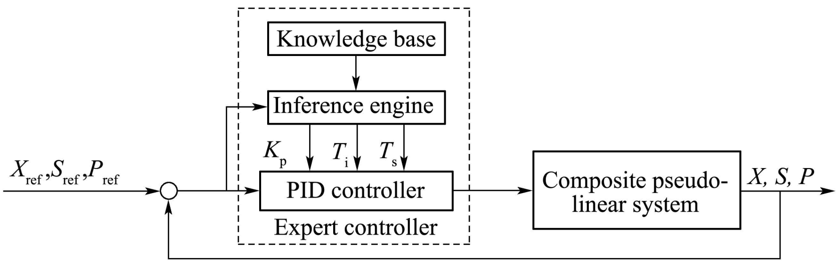


Fig. 2 Principle of expert controller

Figure 3 shows the closed-loop setup of this decoupling control strategy.

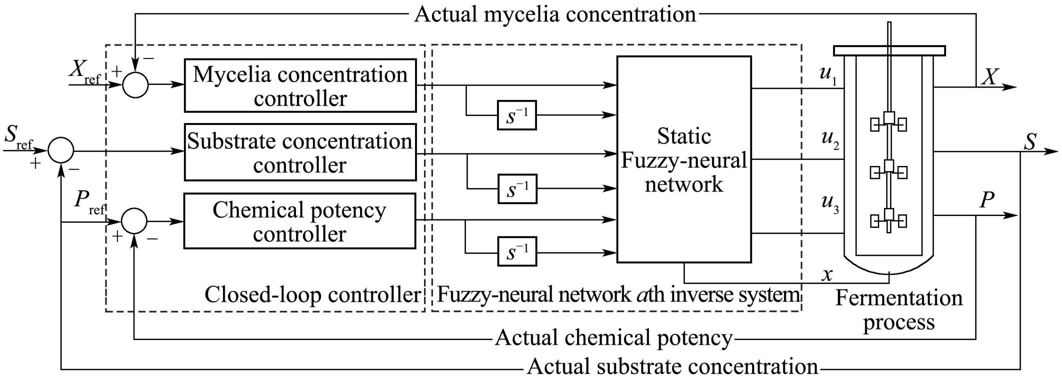


Fig. 3 Closed-loop structure of bioprocess using fuzzy-neural network αth-order inverse decoupling control

5 Experiment research

In the experiment, sample data sets are $\{\dot{X}, X, \dot{S}, S, \dot{P}, P\}$ and $\{u_1, u_2, u_3\}$, which respectively are the input and output of fuzzy-neural networks. $\boldsymbol{u} = (f_{\rm ph}, f_{\rm c}, f_{\rm n})^{\rm T}$ and $\boldsymbol{x} = (X, S, P, V)^{\rm T}$ are taken from bioprocess database. Data set $\{\dot{X}, \dot{S}, \dot{P}\}$ is computed offline using seven decimal numerical algorithm.

The sample data sets are divided into five batches, each of which contains 70 samples. The former four batches are used to train the fuzzy-neural network and the last batch is used to verify the identification results. Fig. 4 shows the identification results.

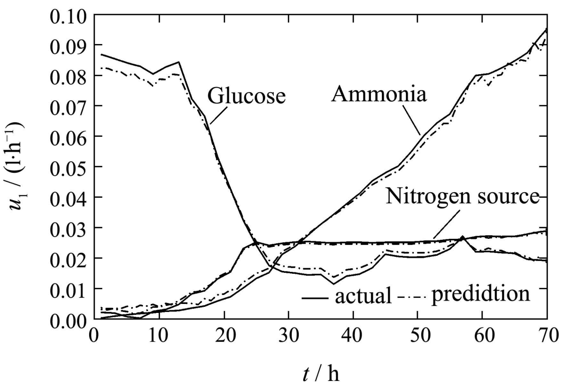
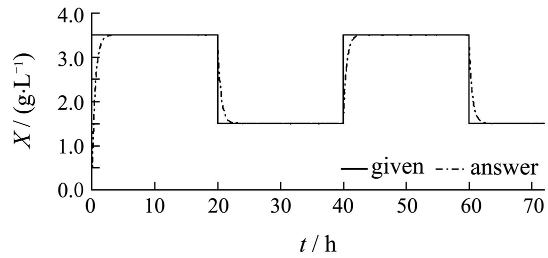
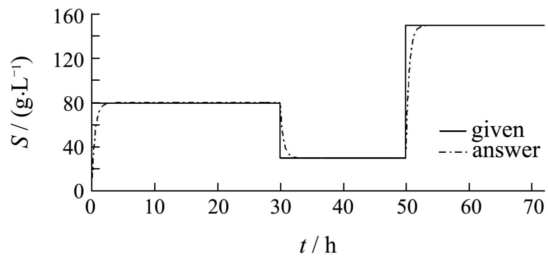


Fig. 4 Identification results of fuzzy-neural network inverse model

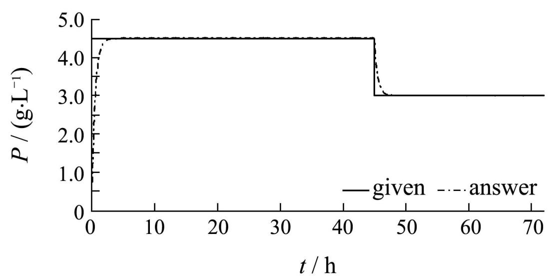
Placing the identified fuzzy-neural network αth-order inverse system in cascade with the biprocess and constructing closed-loop expert PID controllers result in three decoupled SISO systems. The tracking performance of the closed-loop system is illustrated in Fig. 5, which shows the effectiveness of our method.



(a) Mycelia concentration



(b) Substrate concentration



(c) Chemical potency

Fig. 5 Response of the pseudo-linear composite system

6 Conclusion

This paper proposed a fuzzy-neural network αth-order inverse method for such complex systems. In the design procedure, sample data set is used to train a fuzzy-neural network to obtain the inverse system, and exact knowledge of mathematical model is not required. Placing the trained fuzzy-neutral network inverse model in series with the plant results in three decoupled integral system which can be easily synthesized using linear control theory. An experiment shows that our method is effective.

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