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Fuzzy NN based predictive control and its application to green liquor system*

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Abstract: The fuzzy NN predictive control algorithm introduced in this paper uses fuzzy neural network to model the nonlinear MIMO process. Its training method that integrates LS and BP algorithm brings quick convergence. GPC algorithm is used as the predictive component. The fuzzy neural network has six layers, including input layer, output layer and four hidden layers. An application to a MIMO nonlinear process(green liquor system of the recovery system in a pulp factory shows that this algorithm has better performance than normal PID algrithm.

Key words: model predictive control, fuzzy neural networks, generalized predictive control
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INTRODUCTION

With rapid progress in fuzzy theory and neural networks, many algorithms that combine fuzzy system or neural networks with model predictive control appeared. Most of them use nonlinear optimization methods to calculate the manipulated variables, including FSQP (Wang et al., 1991), or Branch and Bound (Sousa et al., 1997). But FSQP algorithm may fall into local minimum, and need large amount of calculations. Branch and Bound method can yield global minimum theoretically, but requires the calculation when the problem becomes more complicated.

This paper introduces a model predictive control algorithm, which use Takagi-Sugeno type fuzzy neural network model and GPC algorithm to calculate the manipulated variables according to the local linear model generated by the fuzzy neural network model. The simulation of green liquor system shows that this algorithm performs well.

FUZZY NEURAL NETWORK MODEL

The Takagi-Sugeno type fuzzy model that can be applied to an n-input, n-output MIMO system is composed of the N rules listed as:

R_i: if $x_1(t)$ is V_1^i and $x_2(t)$ is $V_2^i \cdots$ and $x_n(t)$ is V_n^i then

$$\begin{aligned} X_i(t+1) = {} & \alpha_{i1} X(t) + \alpha_{i2} X(t-1) + \\ & \cdots + \alpha_{ip} X(t-p+1) + \\ & \beta_{i1} U(t) + \beta_{i2} U(t-1) + \\ & \cdots + \beta_{iq} U(t-q+1) \end{aligned} \tag{1}$$

where

$$\begin{aligned} & X(t) = [x_1(t) \ x_2(t) \ \cdots \ x_n(t)]^{\mathrm{T}} \\ & U(t) = [u_1(t) \ u_2(t) \ \cdots \ u_n(t)]^{\mathrm{T}} \\ & \alpha_{ij} = [\alpha_{ij1} \ \alpha_{ij2} \cdots \ \alpha_{ijn}]^{\mathrm{T}} \\ & \beta_{il} = [\beta_{il1} \ \beta_{il2} \cdots \ \beta_{iln}]^{\mathrm{T}} \\ & i = 1, 2, \cdots, N; \ j = 1, 2, \cdots, p; \ l = 1, 2, \cdots, q. \end{aligned}$$

Use of the product operation reasoning method and the Center of the Area (COA) defuzzification method yielded the final output of the fuzzy system as:

$$X(t+1) = \frac{\sum_{i=1}^{N} X_i(t+1) \prod_{d=1}^{n} \mu_{V_d^i}(x_d(t))}{\sum_{i=1}^{N} \prod_{d=1}^{n} \mu_{V_d^i}(x_d(t))} \tag{2}$$

A neural network appropriate for training can

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be integrated into the above fuzzy system (Roger Jang, 1993). Fig.1 shows a two inputs two outputs fuzzy neural network, where input variable x_1 is partitioned into three fuzzy sets and input variable x_2 is partitioned into two fuzzy sets.

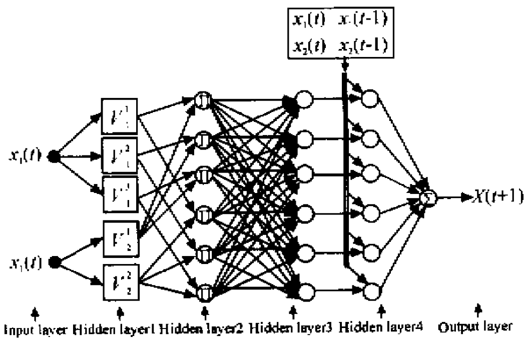

Fig.1 The structure of the fuzzy neural network with two inputs and two outputs

The network has six layers, including input layer, output layer and four hidden layers.

1) Input layer: Connects directly with the input variables and transfers them to next layers.

2) Hidden layer 1: Its output is defined as:

$$O_{1,i1} = \mu_{V_d^i}(x_d(t)) \tag{3}$$

where $x_d(t)$ is the input of the node, V_d^i is the related fuzzy set, $i1 \in \{1, 2, \cdots, L_1\}$. L_1 is the number of the nodes of this layer, L_2, L_3, L_4 mentioned later is the number of the nodes of the relevant layer respectively. $\mu_{V_d^i}$ is the Gauss membership function:

$$\mu_{V_d^i}(x_d(t)) = \exp\left(\frac{-(x_d^i - \bar{x}_d^i)^2}{2(\delta_d^i)^2}\right) \tag{4}$$

3) Hidden layer 2: The output of this layer is the product of the input of the node, which defined as:

$$O_{2,i2} = \prod_{i1=1}^{L_1} O_{1,i1} \text{ where } i2 \in \{1, 2, \cdots, L_2\} \tag{5}$$

4) Hidden layer 3: This layer is based on Center of the Area (COA) defuzzification method, and is defined as:

$$O_{3,i3} = \frac{O_{2,i2}}{\sum_{i2=1}^{L_2} O_{2,i2}} \text{ where } i3 \in \{1, 2, \cdots, L_3\} \tag{6}$$

5) Hidden layer 4: The output of this layer is defined as:

$$O_{4,i4} = X_i(t+1) * O_{3,i3} \text{ where } i4 \in \{1, 2, \cdots, L_4\} \tag{7}$$

6) Output layer: This layer sums its input and is defined as:

$$O_5 = \sum_{i4=1}^{L_4} O_{4,i4} = X(t+1) \tag{8}$$

Assume the expected output is $X_c(t+1)$. Considering that there are Q data pairs, the objective function is given by

$$J_1 = \sum_{h=1}^{Q} \| X_{ch}(t+1) - X_h(t+1) \|^2. \tag{9}$$

A hybrid method is used for training the network: Least Square algorithm is used to determine the local model parameters (defined in the conclusion part of Eq.(1); BP algorithm is used to adjust the center and the shape of the membership function.

After the identification procedure showed above, N local linear models are obtained, namely

$$\begin{aligned} X_i(t+1) = {} & \alpha_{i1} X(t) + \alpha_{i2} X(t-1) + \\ & \cdots + \alpha_{ip} X(t-p+1) + \\ & \beta_{i1} U(t) + \beta_{i2} U(t-1) + \\ & \cdots + \beta_{iq} U(t-q+1) \end{aligned} \tag{10}$$

Rewrite Eq.(10) as

$$A_i(z^{-1}) X_i(t+1) = B_i(z^{-1}) U_i(t) \tag{11}$$

Assume that the cost function is

$$\begin{aligned} J_{pi} = {} & \sum_{j=1}^{P_i} \| X(t+j) - X_r(t+j) \|_2 + \\ & \sum_{j=1}^{M_i} \| X(t+j) - X_r(t+j) \|_2 \end{aligned} \tag{12}$$

where P_i is predictive horizon, M_i is control horizon.

According to the GPC (Clarke, et al., 1987) algorithm, minimize the cost function to get the control law, name it as $\Delta U_i(t+1)$. Then rewrite Eq.(1) as

R_i: if $x_1(t)$ is V_1^i and $x_2(t)$ is $V_2^i \cdots$ and $x_n(t)$ is V_n^i then

$$\begin{aligned} X_i(t+1) = {} & \alpha_{i1} X(t) + \alpha_{i2} X(t-1) + \\ & \cdots + \alpha_{ip} X(t-p+1) + \\ & \beta_{i1} U(t) + \beta_{i2} U(t-1) + \\ & \cdots + \beta_{iq} U(t-q+1) \end{aligned} \tag{13}$$

and the increment of manipulated variables is $\Delta U_i(t+1)$ where

$$\Delta U(t+1)=\frac{\sum_{i=1}^{N}\Delta U_i(t+1)\prod_{d=1}^{n}\mu_{V_d^i}(x_d)}{\sum_{i=1}^{N}\prod_{d=1}^{n}\mu_{V_d^i}(x_d)} \quad (14)$$

SIMULATION

Green liquor system is a part of the recovery system of a pulp factory. After vaporizing, the black liquor burns in the recovery boiler, the smelt generated during burning (the main components including Na_2CO_3 and Na_2S) dissolves in the weak liquor and becomes green liquor. The green liquor will be causticized to recycle the alkali (See Fig.2).

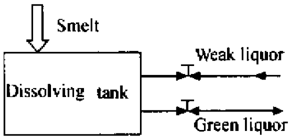

Fig.2 The green liquor system

Fig.3 shows the step response of the green liquor system when using fuzzy neural network predictive controller. Fig. 4 shows the results when using traditional PID controller. It is obvious that the former has better performance.

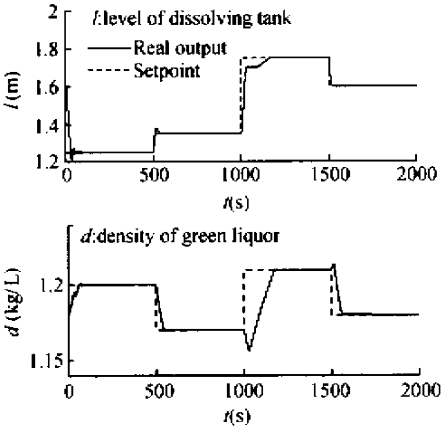

Fig.3 System response when using fuzzy NN predictive controller

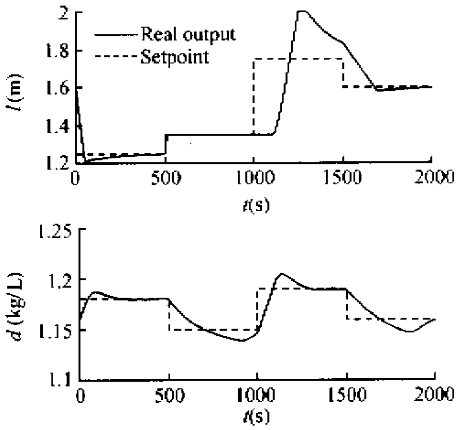

Fig.4 System response when using PID controller

CONCLUSIONS

This paper introduced a fuzzy NN predictive control algorithm, using fuzzy neural network as the model of nonlinear MIMO system, and a hybrid training method (integrating BP and LS algorithm) to improve the efficiency. This algorithm requires less calculation and is easy to tune, compared with normal nonlinear predictive control algorithm. The simulation results showed that the FNNPC algorithm has good performance and is suitable for industrial applications.

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