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Nonlinear Predictive Control Using Fuzzy Hammerstein Model and Its Application to CSTR Process

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Abstract

A fuzzy-Hammerstein model predictive control method is proposed for a continuous stirred-tank reactor (CSTR). In this paper T-S fuzzy model is used to approximate the static nonlinear characteristics of Hammerstein model, and a linear autoregressive model is used to solve the results of optimal control. The designed nonlinear predictive controller using Hammerstein model make good use of the ability of universal approach nonlinear of T-S model, and divide the question of nonlinear predictive control into the nonlinear model recongnization and the question of linear predictive control. The application results of CSTR process show the proposed control method has good control performance compared to PID controller.

Keywords: Hammerstein mode, T-S Fuzzy model, Nonlinear predictive control, CSTR

1. Introduction

Nonlinear systems widely exist in the actual production process, and control methods for nonlinear systems are endless, predictive control as a novel control algorithm has been extensive research by scholars from various countries[1]. Many predictive control algorithms based on neural network models[2], fuzzy models[3] with nonlinear approximation ability have been proposed. And there are also experiment mode-

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based predictive control algorithms, such as Hammerstein model[4], Wiener model[5], Volterra model[6]. Hammerstein model as a kind of experimental model, has to describe the characteristics of various types of nonlinear object, literature [7] using a polynomial model to approximate the nonlinear characterristcs of Hammerstein model, the linear part of the external factors input autoregressive model (Autoregressive the model with exogenous input ARX) Description and Binary Distillation the tower simulation results show that the effectiveness of the method, but using polynomial to describe nonlinear makes the precision and complexity of the algorithm is proportional to the increase, has certain limitations. In the literature [8] using nonlinear base as static nonlinear part of the Hammerstein model, while its dynamic linear part Laguerre series, this method may effectively control the output of the interference, and pH neutralization process to prove the algorithm is effictive. Zhu[9] and others Hammerstein model has been improved, and the algorithm is verified by simulation better control effect. In [10] for the CSTR reactor two new identification are introduced based on Hammerstein model identification are given, and good control method given. In literature [11] nonlinear predictive control algorithms based on Hammerstein model to demonstrate the stability and robustness of the algorithm, and pH and reaction process example simulation.

The main work of the paper is based on the Hammerstein model, the nonlinear static part using T-S fuzzy model has strong nonlinear approximation ability, the control object recognition, dynamic linear part of Hammerstein model solution by ARX (Auto regression model with exogenous input) optimal control, in order to achieve continuous stirred tank reactor (CSTR) cascade model of stability control.

2. Fuzzy Hammerstein model and its description

Hammerstein model can use figure 1 shows the structure to said. Using this model can realize static nonlinear identification problems and dynamic linear optimization solving problem.

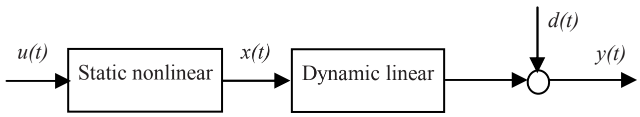

Fig.1 Structure diagram of Hammerstein model

In the paper the static nonlinear Hammerstein model part uses T-S fuzzy model distinguish controlled object model parameters, dynamic linear part adopts external input autoregressive model (ARX) to solve optimal control law.

Static nonlinear part is described as

$$x(t) = f[x(t), u(t)] + \zeta(t) = f[x(t-1), \cdots, x(t-nx), u(t-1), \cdots, u(t-nu)] + \zeta(t) \tag{1}$$

Dynamic linear part adopts ARX structure：

$$C(q^{-1})y(t) = q^{-d} D(q^{-1})x(t) \tag{2}$$

where *y(t), u(t)*, $\zeta(t)$ are the system output, input and uncertain disturbance, respectively. *nx* and *nu* are the orders of the system intermediate variables and inputs. $f[\cdot]$ is a piecewise continuous nonlinear function. The model of nonlinear part uses T-S fuzzy model to describe:

if $x(t-1)$ is $\mu_{i,1}, \cdots, x(t-nx)$ is $\mu_{i,nx}$, $u(t-1)$ is $\mu_{i,nx+1}, \cdots, u(t-nu)$ is $\mu_{i,nx+nu}$ then

$$x_i(t) = A_{i,r}x(t) + B_{i,r}u(t) + \zeta(t) \tag{3}$$

where $\mu_{i,l}$ denotes the *l*th fuzzy variable of the *i*th fuzzy rule, $i = 1, \cdots, L$; L denotes the fuzzy rules number,

$$\mu_{i,l} = \mu_{i,l}[x(t-l)] \quad l = 1, \cdots, nx \;,\; \mu_{i,l} = \mu_{i,l}[u(t+nu-l)] \quad l = nx+1, \cdots, nx+nu$$

$$A_{i,r}(q^{-1}) = a_{i,1}q^{-1} + a_{i,2}q^{-2} + \cdots + a_{i,nx}q^{-nx} \quad B_{i,r}(q^{-1}) = b_{i,1}q^{-1} + b_{i,2}q^{-2} + \cdots + b_{i,nu}q^{-nu}$$

If the linear model (3) is seen as a subsystem of the fuzzy model, the output of the system (1) may be described as the weighted average of the output fuzzy subsystems.

$$x(t)=\sum_{i=1}^{L} g_i(t)x_i(t) \tag{4}$$

where $g_i(t)=\mu_i(t)\Big/\sum_{i=1}^{L}\mu_i(t)$, $\sum_{i=1}^{L} g_i(t)=1$, $\mu_i(t)=\prod_{l=1}^{nx+nu}\mu_{i,l}$ is the membership degree of the ith fuzzy rules. Π denotes fuzzy operator, usually take a small or product operation.

Substituting Eq.(3) into Eq.(4), the system output can be written as:

$$x(t)=\sum_{i=1}^{L} g_i(t)[A_{i,r}x(t)+B_{i,r}u(t)]+\zeta(t)=\sum_{i=1}^{L} g_i(t)[a_{i,1}x(t-1)+a_{i,2}x(t-2)+\cdots+b_{i,1}u(t-1)+\cdots+b_{i,nu}u(t-nu)]+\zeta(t) \tag{5}$$

Eq. (5) can be written in matrix form:

$$X(t) = F\tilde{X}(t)+HU(t) \tag{6}$$

where

$$F=\begin{bmatrix} f_{1,1}\cdots f_{1,nx} \\ \vdots \ \ddots \ \vdots \\ f_{L,1}\cdots f_{L,nx}\end{bmatrix},\ H=\begin{bmatrix} h_{1,1}\cdots h_{1,nu} \\ \vdots \ \ddots \ \vdots \\ h_{L,1}\cdots h_{L,nu}\end{bmatrix},\ f_{i,j}=g_i(t)a_{i,j}\ ,i=1,\cdots,L,j=1,\cdots,nx\ ,h_{i,j}=g_i(t)b_{i,j}\ ,i=1,2,\cdots,L,j=1,2,\cdots,nu$$

$\tilde{X}(t)=[x(t-1),x(t-2),\cdots,x(t-nx)]^{\mathrm{T}}$ $U(t)=[u(t-1),u(t-2),\cdots,u(t-nu)]^{\mathrm{T}}$

The dynamic linear part may be described as the following ARX model:

$$C(q^{-1})y(t) = q^{-d}D(q^{-1})x(t) \tag{7}$$

where $C(q^{-1})=1+c_1q^{-1}+\cdots+c_nq^{-n}$, $D(q^{-1})=d_1q^{-1}+d_2q^{-2}+\cdots+d_mq^{-m}$

Set d=0, and multiply $\Delta=1-q^{-1}$ at both sides, Eq.(7) is given

$$\tilde{C}(q^{-1})y(t) = D(q^{-1})\Delta x(t) \tag{8}$$

where $\tilde{C}(q^{-1})=(1-q^{-1})C(q^{-1})=1+\tilde{c}_1q^{-1}+\cdots+\tilde{c}_nq^{-n}+\tilde{c}_{n+1}q^{-(n+1)}$, then Eq. (8) is written to the following form

$$y(t)=\sum_{i=1}^{n+1}(-\tilde{c}_i)y(t-i)+\sum_{j=1}^{m}d_j\Delta x(t-j) \tag{9}$$

Taking the current time t, the output of the current moment of $y(t)$, model k steps output by the following Formula

$$\hat{y}(t+k)=\sum_{i=1}^{n+1}\tilde{c}_{k,i}y(t+1-i)+\sum_{j=2}^{m}d_{k,j}\Delta x(t+1-j)+\sum_{l=1}^{k}d_{k-l+1}\Delta x(t+l-1)=\hat{y}_m(t+k)+\sum_{l=1}^{k}d_{k-l+1}\Delta x(t+l-1) \tag{10}$$

where

$$\hat{y}_m(t+k)=\sum_{i=1}^{n+1}\tilde{c}_{k,i}y(t+1-i)+\sum_{j=2}^{m}d_{k,j}\Delta x(t+1-j) \tag{11}$$

Assumption, the forecast modeling error remains unchanged in the time domain, then

$$e(t)=y(t)-\hat{y}(t)$$

where $y(k),\hat{y}(k)$ are k moment process output and model output respectively, the k step predictive output is written to

$$y_c(t+k) = \hat{y}(t+k) + e(t) \quad k = 1, 2, \cdots, p$$

According to the principle of MPC algorithm, a reference trajectory y_r is supposed to be a first-order index form, such as Eq. (12) shows:

$$\begin{cases} y_r(t+k) = \alpha y_r(t) + (1-\alpha) y_{sp} & k = 1, 2, \cdots, p \\ y_r(t) = y(t) \end{cases} \tag{12}$$

where y_r is a reference trajectory, $\alpha = e^{-T_s/T_r}$, T_s is a sampling period, T_r is a reference trajectory response time, y_{sp} is a set point, y is the process output.

Define

$\hat{Y}(t) = [\hat{y}(t+1) \cdots \hat{y}(t+p)]^{\mathrm{T}}$, $\hat{Y}_c(t) = [\hat{y}_c(t+1) \cdots \hat{y}_c(t+p)]^{\mathrm{T}}$, $Y_r(t) = [y_r(t+1) \cdots y_r(t+p)]^{\mathrm{T}}$,

$\hat{Y}_m(t) = [\hat{y}_m(t+1) \cdots \hat{y}_m(t+p)]^{\mathrm{T}}$, $\Delta X(t) = [\Delta x(t) \quad \Delta x(t+1) \quad \cdots \quad \Delta x(t+M-1)]^{\mathrm{T}}$

$$G = \begin{bmatrix} d_{1,1} & & 0 \\ d_{2,1} & d_{1,1} & \\ \vdots & \vdots & \ddots \\ d_{p,1} & d_{p-1,1} & \cdots & d_{p-M+1,1} \end{bmatrix}$$

where p denotes the prediction steps, M denotes the control steps, then

$$\hat{Y}(t) = \hat{Y}_m(t) + G\Delta X(t) \tag{13}$$

Take the following quadratic target function:

$$J = \min_{\Delta x(t)} \left\{ [Y_c(t) - Y_r(t)]^{\mathrm{T}} Q [Y_c(t) - Y_r(t)] + \Delta X^{\mathrm{T}}(t) R \Delta X(t) \right\} \tag{14}$$

where Q, R denote the positive definite output and control weighted matrix, respectively.

Substituting Eq. (12) and Eq. (13) into the target Eq. (14), then the optimal control law is obtained:

$$\Delta X(t) = [G^{\mathrm{T}} Q G + R]^{-1} G^{\mathrm{T}} Q [Y_r(t) - \hat{Y}_m(t)] \tag{15}$$

At the next sampling interval, the control steps are shifted forward by one step, and the same process computations are repeated. The optimal control function $x(k)$ in current moment is

$$x(t) = x(t-1) + \Delta x(t) \tag{16}$$

Since the control law obtained of Eq.(16) is an intermediate variable, the need to solve the optimal control amount $U(t)$. Substituting Eq. (6) into Eq. (15), the optimal control law can be obtained

$$U(t) = (H^{\mathrm{T}} H)^{-1} H^{\mathrm{T}} [X(t) - F\tilde{X}(t)] \tag{17}$$

The optimal control function $x(k)$ in current moment is

$$u(t) = (H^{\mathrm{T}} H)^{-1} H^{\mathrm{T}} [x(t) - F\tilde{x}(t)] \tag{18}$$

3. Its Application to CSTR Process

In this section, a CSTR (continuous stirred tank reactor) process is used to prove the excellent control performance of the proposed NMPC method based on T-S Fuzzy Hammerstein model. Assuming this CSTR process is an irreversible exothermic reaction, the input and output dynamic equation as follows:

$$\frac{\mathrm{d}C_A}{dt} = \frac{v(t)}{V}[C_{A0}(t) - C_A(t)] - k_0 C_A(t) \exp\left(-\frac{E}{RT(t)}\right),$$

$$\frac{dT}{dt}=\frac{v(t)}{V}\left(T_0(t)-T(t)\right)-\frac{(-\Delta H)k_0}{\rho C_P}C_A(t)\exp\left(-\frac{E}{RT(t)}\right)\frac{\rho_C C_{PC}}{\rho C_P V}q_C(t)\left[1-\exp\left(\frac{-h_A}{q_C(t)\rho_C C_{PC}}\right)\right]\left[T_{c0}(t)-T(t)\right]$$

where C_A denotes the concentration of reactants A; T denotes reaction temperature; q denotes feed flow rate, v_C denotes coolant flow rate.

In order to verify the superiority and effectiveness of the proposed algorithm, PID control algorithms and the proposed algorithm were compared. In Simulation, PID control parameters: K_p=10; K_i=50; K_d=0.5, the parameters of the proposed algorithm were taken: the prediction steps H=8, the response time of the reference trajectory $T_r = 20$ s, the sampling time T_s=1s， $Q = 100\boldsymbol{I}$, R=0.2$\boldsymbol{I}$, where $\boldsymbol{I}$ is corresponding dimension of the unit matrix. The simulation results are shown in Fig. 2-3.

Fig. 2 is PID control algorithm simulation results, when the reactant concentration set value is less than 0.13 to achieve a better control of CSTR process, when the setting value is greater than or equal to 0.13, the output of the model appears obvious oscillation, so change when the CSTR process operation range is large, PID control algorithm is difficult to achieve effective control. Fig. 3 for the proposed control algorithm, seen from the figure, the greater change occurred when the concentration of the reactants , the system output may still be able to better track setting, the simulation results significantly better than the first two methods, thus validating the Hammerstein model nonlinear approach to achieve the control of nonlinear systems. Therefore, validation of the algorithm for CSTR reaction such strongly nonlinear process can achieve effective control.

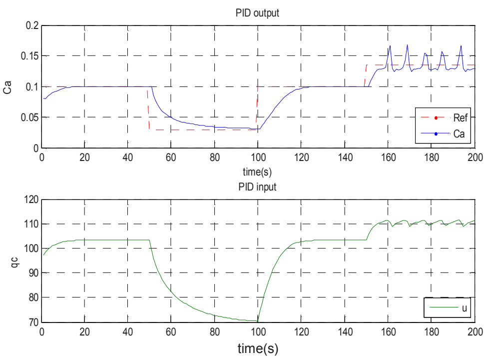

Fig.2 Simulation result of PID control algorithm

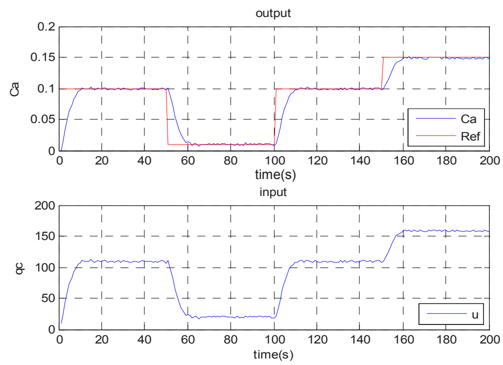

Fig.3 Simulation result of predictive control algorithm based on Hammerstein model

4. Conclusion

In this paper, for strongly nonlinear processes in the chemical industry a nonlinear predictive control method based on fuzzy model is proposed, and applied to the CSTR process. Simulation results show that the proposed method with the conventional PID control algorithm compared to the strong anti-disturbance ability, robustness, and the algorithm is simple, easy to implement, has a practical application.

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