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Generalized Predictive Control of Nonlinear Systems of the Hammerstein Form*

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Abstract: A nonlinear generalized predictive control scheme based on a Hammerstein model is presented in this paper. The stability of the closed-loop system is analyzed with the control horizon equal to one. An adaptive nonlinear generalized predictive control algorithm with a linear estimator is proposed. The simulation examples demonstrate the effectiveness of the algorithm.

Key words: nonlinear system; predictive control; adaptive control; stability

1 Introduction

Generalized predictive control (GPC) based on linear models has enjoyed a growing attention in this last few years[1~7]. The experimental studies and practical applications have demonstrated satisfactory control performance of GPC[8]. However, most plants to be controlled have some kind of nonlinearity. Thus the attention should be given to extend GPC control schemes to nonlinear systems. One of these extensions was first introduced in [9], where the GPC scheme was used to control a plant described by a Hammerstein model. Due to the fact that the linear and nonlinear parts of the system were considered separately in [9], the stability of the closed-loop system is hard to analyze; besides, a nonlinear estimation scheme had to be used in their adaptive algorithm. In this paper, a nonlinear GPC control based on a Hammerstein model is considered. Somewhat different from the work presented in [9] a new cost function is used for the controller design, and stability analysis of the closed-loop system is carried out with the control horizon equal to one. An adaptive nonlinear generalized predictive control algorithm with a linear estimation scheme (ANGPC) is also proposed.

2 Controller Design

The plant to be controlled is assumed to be representable by a discrete-time Hammerstein model of the form

$$A(z^{-1})y(t) = B(z^{-1})x(t-1) + C(z^{-1})\omega(t)/\Delta \tag{2.1}$$

where $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are polynomials in the backward shift operator z^{-1} of the form

$$A(z^{-1}) = 1 + a_1 z^{-1} + \cdots + a_n z^{-n},$$

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$$B(z^{-1}) = b_0 + b_1 z^{-1} + \cdots + b_m z^{-m},$$
$$C(z^{-1}) = 1 + c_1 z^{-1} + \cdots + c_l z^{-l}.$$

The static nonlinearity is given by

$$x(t) = r_0 + r_1 u(t) + r_2 u^2(t) + \cdots + r_p u^p(t) \tag{2.2}$$

where p is odd. $\{u(t)\}$ and $\{y(t)\}$ are the plant input and output sequences respectively. $\Delta = 1 - z^{-1}$ is the difference operator. Notice that the model (2.1) has the advantage that the controller will naturally contain an integrator[3]. The sequence $\{\omega(t)\}$ is a stochastic process defined on a probability space $\{\Omega, \mathcal{F}, P\}$ on which a sequence of increasing sigma algebras is denoted by $(\mathcal{F}_t, t \in N)$ where $\mathcal{F}_t$ is generated by the observations up to and including time t. The sequence $\{\omega(t)\}$ is assumed to satisfy

$$E\{\omega(t)/\mathcal{F}_{t-1}\} = 0, \quad \text{a.s.} \tag{2.3}$$
$$E\{\omega(t)^2/\mathcal{F}_{t-1}\} = \sigma^2, \quad \text{a.s.} \tag{2.4}$$
$$\limsup_{N\to\infty} \frac{1}{N}\sum_{t=1}^{N}\omega(t)^2 < \infty. \quad \text{a.s.} \tag{2.5}$$

The cost function has the following form

$$J = E\{\sum_{j=1}^{N_1}(y(t+j) - y_r(t+j))^2 + \lambda\sum_{j=1}^{N_1}(\Delta u^p(t+j-1))^2 | \mathcal{F}_t\} \tag{2.6}$$

where $\{y_r(t)\}$ is a known bounded set-point sequence, N_1 is the prediction horizon whereas λ is a weighting constant. The expectation in (2.6) is made given data obtained up to time t. The cost on $\Delta u^p(t)$ is physically meaningful, since $\Delta u^p(t)$ is monotonically increasing, thus it penalizes changes in the control action.

For the sake of simplicity, assume $C(z^{-1}) = 1$, Note, however, that the method can readily cope with coloured noise. Using the following polynomial equations

$$1 = F_j(z^{-1})A(z^{-1})\Delta + z^{-j}G_j(z^{-1}), \tag{2.7}$$
$$B(z^{-1})F_j(z^{-1}) = E_j(z^{-1}) + z^{-j}H_j(z^{-1}), \tag{2.8}$$

where $j = 1, 2, \cdots, N_1$ and

$$F_j(z^{-1}) = f_0 + f_1 z^{-1} + \cdots + f_{j-1} z^{-j+1},$$
$$G_j(z^{-1}) = g_0^j + g_1^j z^{-1} + \cdots + g_n^j z^{-n},$$
$$E_j(z^{-1}) = e_0 + e_1 z^{-1} + \cdots + e_{j-1} z^{-j+1},$$
$$H_j(z^{-1}) = h_0^j + h_1^j z^{-1} + \cdots + h_{m-1}^j z^{-m+1}.$$

the plant equation (2.1) can be written in the form

$$y(t+j) = E_j\Delta x(t+j-1) + G_j y(t) + H_j\Delta x(t-1) + F_j\omega(t+j) \tag{2.9}$$

where $j = 1, \cdots, N_1$.

Using (2.2) the equation (2.9) can be written in the vector from

$$\boldsymbol{y} = E\sum_{i=1}^{p} r_i \boldsymbol{u}_i + Gy(t) + H\sum_{i=1}^{p} r_i \Delta u^i(t-1) + F \tag{2.10}$$

where

$$\boldsymbol{y}^{\mathrm{T}} = [y(t+1), \cdots, y(t+N_1)],$$
$$\boldsymbol{u}_i^{\mathrm{T}} = [\Delta u^i(t), \Delta u^i(t+1), \cdots, \Delta u^i(t+N_1-1)],$$

$$G^{\mathrm{T}} = [G_1, \cdots, G_{N_1}], \quad H^{\mathrm{T}} = [H_1, \cdots, H_{N_1}],$$
$$F^{\mathrm{T}} = [F_1\omega(t+1), \cdots, F_{N_1}\omega(t+N_1)] \tag{2.11}$$

and where E is the $N_1 \times N_1$ lower-triangular matrix

$$E = \begin{bmatrix} e_0 & & & \\ e_1 & e_0 & & \\ \cdots & & \ddots & \\ e_{N_1-1} & e_{N_1-2} & \cdots & e_0 \end{bmatrix}. \tag{2.12}$$

Define $$y_r^{\mathrm{T}} = [y_r(t+1), \cdots, y_r(t+N_1)].$$

From the definition of y, y_r and u_i the cost function (2.6) can be written as

$$J = E\{(y - y_r)^{\mathrm{T}}(y - y_r) + \lambda u_p^{\mathrm{T}} u_p \mid \mathscr{F}_t\}. \tag{2.13}$$

Substituting (2.10) into (2.13), differentiating J with respect to u_p and putting the result to equal to zero yield

$$(r_p I + \sum_{i=1}^{p-1} r_i \frac{\partial u_i^{\mathrm{T}}}{\partial u_p}) E^{\mathrm{T}} (E \sum_{i=1}^{p} r_i u_i + G y(t) + H \sum_{i=1}^{p} r_i \Delta u^i(t-1) - y_r) + \lambda u_p = 0. \tag{2.14}$$

If we ignore the dependence of $u_i (i = 1, \cdots, p-1)$ on u_p, we obtain

$$r_p E^{\mathrm{T}} (E \sum_{i=1}^{p} r_i u_i + G y(t) + H \sum_{i=1}^{p} r_i \Delta u^i(t-1) - y_r) + \lambda u_p = 0. \tag{2.15}$$

which can be written as

$$r_p E^{\mathrm{T}} E \sum_{i=1}^{p-1} r_i u_i + (r_p^2 E^{\mathrm{T}} E + \lambda I) u_p = r_p E^{\mathrm{T}} (y_r - G y(t) - H \sum_{i=1}^{p} r_i \Delta u^i(t-1)). \tag{2.16}$$

This constitutes a total of N_1 equations with N_1 unknown elements. It is not easy to find a solution for $u(t)$. Note that the control horizon and the output prediction horizon have been selected to be the same, i. e. N_1, in the above analysis. This is not a necessary requirement. A control horizon $N_u < N_1$ can be used [3]. Furthermore, it is possible to put the control horizon $N_u = 1$ in our design of the controller, i. e. $\Delta u^i(t+j) = 0$ $(j = 1, \cdots, N_1 - 1)$. In this case, u_i and E given in (2.11) and (2.12) take the forms, respectively,

$$u_i = \Delta u^i(t), \tag{2.17}$$

$$E^{\mathrm{T}} = [e_0, e_1, \cdots, e_{N_1-1}]. \tag{2.18}$$

Using (2.17) and (2.18) and noting that $z^{-1}u^i(t) = u^i(t-1)$, $(i = 1, \cdots, p)$, equation (2.16) can be rewritten in the form

$$ke \sum_{i=1}^{p-1} r_i u^i(t) + u^p(t) = P(z^{-1}) y_r(t+N_1) - \alpha(z^{-1}) y(t) - \beta(z^{-1}) \sum_{i=1}^{p} r_i \Delta u^i(t-1)$$
$$+ ke \sum_{i=1}^{p-1} r_i u^i(t-1) + u^p(t-1) \tag{2.19}$$

where $$P(z^{-1}) = k(e_{N_1-1} + e_{N_1-2} z^{-1} + \cdots + e_0 z^{-N_1+1}),$$

$$\alpha(z^{-1}) = k \sum_{j=1}^{N_1} e_{j-1} G_j(z^{-1}), \quad \beta(z^{-1}) = k \sum_{j=1}^{N_1} e_{j-1} H_j(z^{-1})$$

where as $k=r_p/(r_p^2e+\lambda)$ and $e=\sum_{i=0}^{N_1}e_i^2$.

Equation (2. 19) is a p'th order Hammerstein polynomial in $u(t)$ which is fairly easy to solve numerically in order to find $u(t)$. For instance, the improved root solving procedure given in [9] can be used, and a real root of minimum magnitude can always be found because p is odd.

3 Stability Analysis

Let us rewrite (2. 19) as

$$(ke+z^{-1}\beta(z^{-1}))\sum_{i=1}^{p-1}r_i\Delta u^i(t)+(1+z^{-1}r_p\beta(z^{-1}))\Delta u^p(t)$$
$$=P(z^{-1})y_r(t+N_1)-\alpha(z^{-1})y(t). \tag{3. 1}$$

From (2. 1) and (2. 2) we have

$$A(z^{-1})\Delta y(t)=z^{-1}B(z^{-1})\sum_{i=1}^{p-1}r_i\Delta u^i(t)+z^{-1}r_pB(z^{-1})\Delta u^p(t)+\omega(t). \tag{3. 2}$$

Lemma 3. 1 For the system

$$T(z^{-1})\Delta u^p(t)=A(z^{-1})y(t+d)+B(z^{-1})\sum_{j=1}^{p-1}r_j\Delta u^j(t)+C(z^{-1})\omega(t),$$

if $T(z^{-1})$ is stable, d is a positive integer and $\omega(t)$ satisfies (2. 5), then

$$\frac{1}{N}\sum_{i=1}^{N}(\Delta u^p(t))^2\leqslant\frac{K_1}{N}\sum_{i=1}^{N}y^2(t+d)+K_2,\quad \text{a. s.}$$

where $0<K_1<\infty$ and $0<K_2<\infty$.

Proof See [12].

Theorem 3. 1 If the control law (2. 19) is used, N_1 and λ are chosen such that

$$T(z^{-1})=A(z^{-1})\Delta(1+z^{-1}r_p\beta(z^{-1}))+z^{-1}r_p\alpha(z^{-1})B(z^{-1}) \tag{3. 3}$$

is stable, then, with probability 1,

1) The resulting closed-loop system will be stable in the sense that $\{\Delta u^i(t)\}$ $(i=1,\cdots,p)$, and $\{y(t)\}$ are sample mean square bounded.

2) The control law (2. 19) minimizes the cost function

$$J'=E\{(P(z^{-1})(y(t+N_1)-y_r(t+N_1))+\lambda'\Delta u^p(t))^2|\mathscr{F}_t\} \tag{3. 4}$$

where $\lambda'=\lambda k/r_p$. Moreover the minimum possible value of the quadratic cost function (3. 4) is

$$\gamma^2=k^2\sigma^2\sum_{j=1}^{N_1}\Big(\sum_{i=0}^{N_1-j}e_{i+j-1}f_i\Big)^2.$$

3) For constant $\{y_r(t)\}$ and $\omega(t)=0$ we have

$$\lim_{t\to\infty}(y(t)-y_r(t))=0.$$

Proof 1) Multiplying (3. 1) by $A\Delta$ and $z^{-1}r_pB$ respectively and using (3. 2) we obtain

$$T\Delta u^p(t)=A\Delta Py_r(t+N_1)-(A\Delta(ke+z^{-1}\alpha B)+z^{-1}\alpha B)\sum_{i=1}^{p-1}r_i\Delta u^i(t)-\alpha\omega(t), \tag{3. 5}$$

$$Ty(t)=z^{-1}r_pBPy_r(t+N_1)+z^{-1}\frac{\lambda}{r_p}kB\sum_{i=1}^{p-1}r_i\Delta u^i(t)+(1+z^{-1}r_p\beta)\omega(t). \tag{3. 6}$$

If $T(z^{-1})$ is stable, from equations (3.5) and (3.6) and using superposition, Lemma 3.1, the assumption (2.5) and the boundness of $\{y_r(t)\}$, one obtains conclusion (1) of the theorem.

2) Multiplying by $r_p E^T$. adding $\lambda \Delta u^p(t)$ on both sides of equation (2.10) and using (2.17) and (2.18) we have

$$r_p E^T y + \lambda \Delta u^p(t) = r_p^2 e \Delta u^p(t) + \lambda \Delta u^p(t) + r_p e \sum_{i=1}^{p-1} r_i \Delta u^i(t)$$
$$+ r_p E^T (G y(t) + H \sum_{i=1}^{p} r_i \Delta u^i(t-1) + F) \tag{3.7}$$

which results in

$$\Delta u^p(t) = P(z^{-1}) y(t+N_1) + \lambda' \Delta u^p(t) - v(t+N_1)$$
$$- \alpha(z^{-1}) y(t) - \beta(z^{-1}) \sum_{i=1}^{p} r_i \Delta u^i(t-1) - ke \sum_{i=1}^{p-1} r_i \Delta u^i(t) \tag{3.8}$$

where
$$v(t+N_1) = k \sum_{j=1}^{N_1} e_{j-1} F_j(z^{-1}) \omega(t+j). \tag{3.9}$$

Define
$$\Phi(t+N_1) = P(z^{-1}) y(t+N_1) + \lambda' \Delta u^p(t). \tag{3.10}$$

Thus (3.8) can be written as

$$\Phi(t+N_1) - v(t+N_1) = \alpha(z^{-1}) y(t) + \beta(z^{-1}) \sum_{i=1}^{p} r_i \Delta u^i(t-1) + \Delta u^p(t) + ke \sum_{i=1}^{p-1} r_i \Delta u^i(t). \tag{3.11}$$

We note that $\Phi(t+N_1) - v(t+N_1)$ is $\mathscr{F}_t$-measurable. It is obvious that $\Phi(t+N_1) - v(t+N_1)$ is the optimal linear prediction of $\Phi(t+N_1)$ given $\mathscr{F}_t$. i. e.

$$\Phi^0(t+N_1) = \Phi(t+N_1) - v(t+N_1)$$
$$= \alpha(z^{-1}) y(t) + \beta(z^{-1}) \sum_{i=1}^{p} r_i \Delta u^i(t-1) + \Delta u^p(t) + ke \sum_{i=1}^{p-1} r_i \Delta u^i(t). \tag{3.12}$$

Now, note that
$$\Phi(t+N_1) = \Phi^0(t+N_1) + v(t+N_1). \tag{3.13}$$

Substituting (3.10) and (3.13) into (3.4) we obtain after some manipulations

$$J' = E\{(\Phi^0(t+N_1) - P(z^{-1}) y_r(t+N_1))^2\} + E\{v(t+N_1)^2 | \mathscr{F}_t\}$$
$$\geqslant E\{v(t+N_1)^2 | \mathscr{F}_t\}. \tag{3.14}$$

The first term on the right-hand side of (3.14) is greater or equal to zero and is brought to zero by

$$\Phi^0(t+N_1) = P(z^{-1}) y_r(t+N_1). \tag{3.15}$$

Substituting (3.12) into (3.15) we have the control law (2.19) immediately.

Finally, from (3.9) we obtain

$$E\{v(t+N_1)^2 | \mathscr{F}_t\} = E\{(k \sum_{j=1}^{N_1} e_{j-1} \sum_{i=0}^{j-1} f_i \omega(t+j-i))^2 | \mathscr{F}_t\}$$
$$= k^2 \sigma^2 \sum_{j=1}^{N_1} \Big(\sum_{i=0}^{N_1-j} e_{i+j-1} f_i \Big)^2 = \gamma^2. \tag{3.16}$$

3) Using (2.7), (2.8) and the definitions of $\alpha(z^{-1})$ and $\beta(z^{-1})$, $T(z^{-1})$ can be written as

$$T = A\Delta(1 - z^{-1}r_p k\sum_{i=1}^{N_1} z^j e_{i-1}E_i) + z^{-1}r_p kB\sum_{i=1}^{N_1} z^j e_{i-1}. \tag{3.17}$$

From (3.17) we have

$$T(1) = r_p kB(1)\sum_{i=1}^{N_1} e_{i-1} = r_p B(1)F(1).$$

Conclusion (3) then follows immediately from (3.6).

4 ANGPC Algorithm

In the previous sections we assummed that the plant parameters were known. When the plant parameters are unknown, a parameter estimator must be used. In this section an adaptive nonlinear generalized predictives control algorithm (ANGPC) is derived by combining the controller give in section 2 with a general parameter estimation scheme. The ANGPC algorithm is based on the following assumptions:

A1) The plant orders n and m in (2.1) are known.

A2) p is a known odd positive integer.

Let us rewrite the plant equation (2.1) as follows

$$A'(z^{-1})y(t) = \sum_{i=1}^{p} B_i(z^{-1})\Delta u_i(t-1) + \omega(t) \tag{4.1}$$

where
$$A'(z^{-1}) = A(z^{-1})\Delta = 1 + a'_1 z^{-1} + \cdots + a'_{n+1}z^{-n-1},$$
$$B_i(z^{-1}) = r_i B(z^{-1}) = b^i_0 + b^i_1 z^{-1} + \cdots + b^i_m z^{-n}, \quad i = 1,\cdots,p.$$

The following polynomial equations are used to calculate $G_j(z^{-1})$, $E_{ij}(z^{-1})$ and $H_{ij}(z^{-1})$:

$$1 = F_i(z^{-1})A'(z^{-1}) + z^{-j}G_j(z^{-1}), \tag{4.2}$$
$$B_i(z^{-1})F_j(z^{-1}) = E_{ij}(z^{-j}) + z^{-j}H_{ij}(z^{-1}), \tag{4.3}$$

where
$$E_{ij}(z^{-1}) = e^i_0 + e^i_1 z^{-1} + \cdots + e^i_{j-1}z^{-j+1},$$
$$H_{ij}(z^{-1}) = h^{ij}_0 + h^{ij}_1 z^{-1} + \cdots + h^{ij}_{m-1}z^{-m+1},$$

and where $i=1,\cdots,p$ and $j=1,\cdots,N_1$.

Define $\quad E^T_i = [e^i_0, e^i_1, \cdots, e^i_{N_1-1}], \quad H^T_i = [H_{i1},\cdots,H_{iN_1}].$

Thus the control law given in (2.19) can be written as

$$E^T_p\sum_{i=1}^{p-1} E_i u_i + (E^T_p E_p + \lambda)u_p = E^T_p(y_r - Gy(t) - \sum_{i=1}^{p} H_i\Delta u^i(t-1)). \tag{4.4}$$

The ANGPC algorithm is now given below.

1) The parameters of system (4.1) are estimated by using the following estimation scheme[10]

$$\theta(t) = \theta(t-1) + \frac{a}{r(t-1)}X(t-1)[y(t) - X(t-1)^T\theta(t-1)], \quad a > 0, \tag{4.5}$$

$$r(t) = r(t-1) + X(t)^T X(t), \quad r(0) = 1 \tag{4.6}$$

where

$$X(t)^T = [y(t),\cdots,y(t-n),\Delta u(t),\cdots,\Delta u(t-m),\cdots,\Delta u^p(t),\cdots,\Delta u^p(t-m)],$$
$$\theta(t)^T = [-a'_1(t),\cdots, -a'_{n+1}(t), b^1_0(t),\cdots,b^1_m(t),\cdots,b^p_0(t),\cdots,b^p_m(t)].$$

2) (4.2) and (4.3) are used to calculate $G_j(z^{-1})$, $E_{ij}(z^{-1})$ and $H_{ij}(z^{-1})$.

3) The control $u(t)$ is determined by solving the equation (4. 4).

Note that a linear estimation scheme is used in our algorithm, whereas a nonlinear estimation scheme must be used in [9] in order to update both the linear part coefficients a_i, b_i and the nonlinear part coefficients r_i.

5 Simulation

In order to investigate the effectiveness of the ANGPC algorithm described in the previous section, some simulation experiments are carried out in this section. For the purpose of comparing the results, the two plants (L1 and L2) and the two nonlinearities (NL1 and NL2) used in the simulated examples in [9] are employed in our simulation experiments. With reference to equation (2. 1) and (2. 2), the following values are used:

L1: $a_1=-0.9$, $b_0=1$, $b_1=2$,

L2: $a_1=-2.87$, $a_2=2.74$, $a_3=-0.87$, $b_0=0.04$, $b_1=0.002$, $b_2=-0.037$,

NL1: $r_0=1$, $r_1=1$, $r_2=1$, $r_3=0.2$,

NL2: $r_0=0$, $r_1=1$, $r_2=1$, $r_3=-1$.

Note that L1 is open-loop stable and nonminimum phase, whereas L2 is open-loop unstable and minimum phase. In addition, $\omega(t)$ in (2. 1) is here a zero-mean random disturbance with covariance $\sigma^2=0.1$.

In order to consider transient behavior, a set-point sequence $y_r(t)$ is assigned as follows:

L1		L2	
samples	set-point value	samples	set-point value
1—20	1	1—40	1
21—40	2	41—80	2
41—60	1	81—120	1
61—80	0	121—160	0

A cycle from 1 to 80 or from 1 to 160 samples is repeated periodically. In each of the Figs. 1~4, the plots given in la, 2a etc. show the actual system output $y(t)$ in an unbroken line whereas the set-point sequence $y_r(t)$ is shown by a broken line. The plots given in 1b, 2b etc. show the control input $u(t)$ by an unbroken line whereas the intermediate variable $x(t)$ is shown by a broken line.

The parameters of the ANGPC algorithm are chosen as N1=3, $\lambda=0.01$ for L1 and $\lambda=0$ for L2. It can be seen from Fig. 1~4 that the system output $y(t)$ tracks the set-point sequence $y_r(t)$ quite well even though there exists a random disturbance. The large initial input and output deviations are due to the effect of an initial estimate of the parameter vector. The predictive nature of the controller can be clearly seen in the plots, where advance knowledge of a set-point value change had caused the actual output signal to start its distinct change before the change in the set-point value has occurred. Comparing with the simulation examples given in [9], it can be seen that rapid variations of the control input $u(t)$ occur in the simulation of L2+NL1 (Fig. 3a) and L2+NL2 (Fig. 4a) in [9], whereas the cotnrol input $u(t)$ is quite smooth in our simulation experiments of L2+NL1 (Fig. 3b) and L2+NL2 (Fig. 4b).

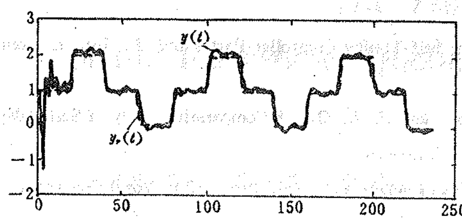

Fig. 1(a) The output $y(t)$ of L1+NL1 and the set-point $y_r(t)$

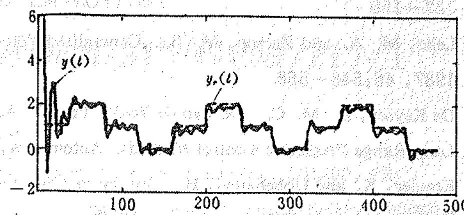

Fig. 1(b) The control $u(t)$ of L1+NL1 and the intermediate variable $x(t)$

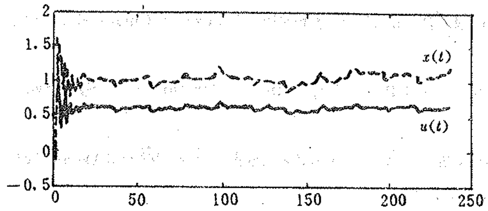

Fig. 2(a) The output $y(t)$ of L1+NL2 and the set-point $y_r(t)$

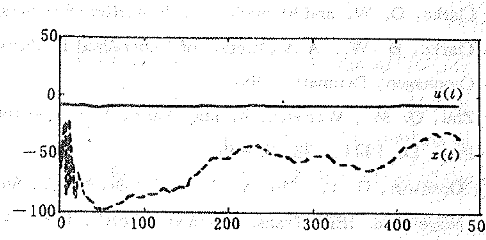

Fig. 2(b) The control $u(t)$ of L1+NL2 and the intermediate variable $x(t)$

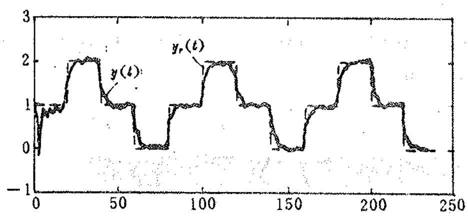

Fig. 3(a) The output $y(t)$ of L2+NL1 and the set-point $y_r(t)$

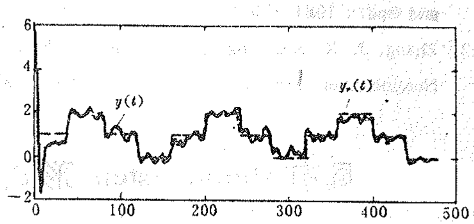

Fig. 3(b) The control $u(t)$ of L2+NL1 and the intermediate variable $x(t)$

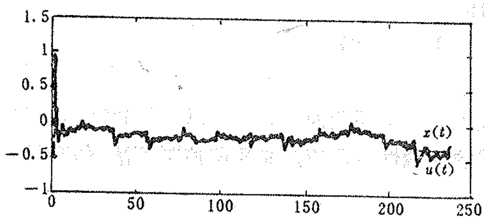

Fig. 4(a) The output $y(t)$ of L2+NL2 and the set-point $y_r(t)$

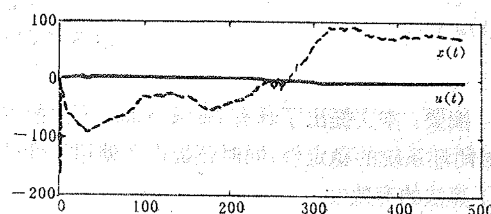

Fig. 4(b) The control $u(t)$ of L2+NL2 and the intermediate variable $x(t)$

6 Conclusion

In this paper a nonlinear generalized predictive control scheme has been presented for systems which can be modelled by a Hammerstein model. A stability result is obtained when the control horizon $N_u=1$. An adaptive nonlinear generalized predictive control algorithm has also been suggested. It should be emphasized that analysis of stability and convergence of nonlinear generalized predictive control schemes in adaptive or self-tuning version is still very difficult.

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具有 Hammerstein 形式的非线性系统广义预测控制

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摘要：本文提出了具有 Hammerstein 形式的非线性系统广义预测控制方法，分析了当控制水平等于1时闭环系统的稳定性，同时还提出了使用线性估计器的非线性自适应广义预测控制算法．仿真结果表明了算法的有效性．

关键词：非线性系统；预测控制；自适应；稳定性

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