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Robust Fuzzy Adaptive Predictive Control

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Abstract: In this paper, we are going to propose an application of fuzzy model and generalized predictive control strategy for the construction of a robust model-based predictive fuzzy controller. A direct adaptive fuzzy model predictive control (DAFMPC) method design is developed for non-linear processes. In this method a GPC controller is used with the Takagi-Sugeno Kang (TSK) piece-wise fuzzy modeling approach. It is shown by simulations that the resulting robust fuzzy adaptive system is stable. The developed method is applied to control a surge tank system.

Keywords: Fuzzy model, robust direct adaptive, non-linear, predictive control

1. INTRODUCTION

Predictive control has become a very important area of research. However, so far few of the presented schemes have been implemented in industrial applications (R. Kennel, A. Linder, 2000). Nevertheless, after some further progress, it can be expected that the advantages of predictive algorithms would lead to an increased number of industrial implementations in the future. An interesting approach to unify the various ideas of predictive control is Generalized Predictive Control (GPC), (Clarke, Mohtadi, Tuffs, 1987; Clarke, Mohtadi, 1989; Clarke, 1994). It generates a sequence of (future) control signals within each sampling interval to optimize the control effort of the controlled system. This is achieved by minimizing a quadratic cost function. Recently, many systematic fuzzy controller design methods have been developed based on the Takagi-Tugeno Kang (TSK) model or the fuzzy dynamic model [1], [2]. Various methodologies that use fuzzy logic to control non-linear systems have been proposed in recent years [linkens et nyongesa 1996]. A common strategy is to use a fuzzy model in a direct adaptive scheme. In this class of controllers, the plant behavior is described over an extended time horizon by fuzzy relational model identified on the basis of closed loop. The main contribution of this paper is the introduction of a predictive controller based on a fuzzy identification algorithm that is more compatible with predictive control schemes. This paper presents a method for designing predictive controllers based on a fuzzy model of the process. In contrast to conventional models, fuzzy models can represent highly nonlinear processes. A new form of DAFMPC, called robust DAFMPC [3], [4]. The proposed MBPC strategy is based on a linear model that linearizes the non linear fuzzy model around the current operating point.

The paper is organized as follows: section 2 deals with the fuzzy model linearization technique and the controller structure. The description of the fuzzy process model is in section 3. Brief introduction to GPC and ordinary discrete time direct adaptive control algorithm with dead zone is reviewed in sections 4, 5 and 6 respectively. Section 7 presents a simulation example to illustrate the proposed adaptive control algorithm, Section 8 concludes the paper.

2. PROBLEM FORMULATION

Many physical systems are very complex in practice so that their rigorous mathematical models can be very difficult if not impossible to obtain. However, many physical systems can indeed be expressed in some form of

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local mathematical models or can be expressed [1, 2] an aggregation of a set of mathematical models. Various fuzzy models have been proposed in the last few years. Here, we consider using the following fuzzy model to represent a complex single-input-single-output (SISO) system that includes both fuzzy inference rules and local analytic linear models [5]:

$$R^i\text{: IF } y(t) \text{ is } B^i \text{ THEN } y(t+1) = a_1^i y(t) + \dots + a_{na}^i\, y(t-na+1) + b_1^i u(t) + \dots + b_{nb}^i\, u(t-n_b+1)$$

$$i = 1, 2, \dots, p \tag{1}$$

where R^i denotes the i^{th} fuzzy inference rule, p the number of inference rules, B^i is a fuzzy set, $u(t)$ the system input variable, $y(t)$ the output of the system, and $a_1^i, \dots, a_{na}^i, b_1^i, \dots b_{nb}^i$ are coefficients of the i^{th} subsystem, and $z(t)=[z_1,\dots,z_p]$ some measurable system variables.

Consider the nonlinear system of the form:

$$\dot{x} = f(x, u) \tag{2}$$

$$y = g(x)$$

where f and g are smooth functions, and $x \in R^n$, $u \in R^m$, and $y \in R$. The plant in reality behaves in some complicated nonlinear fashion. Suppose that its state vector X evolves according to some nonlinear differential equation [6]:

$$\frac{dX}{dt} = f(X, U, t) \tag{3}$$

where U is the vector of inputs. Many processes are naturally described by implicit equations of the form $f(X, dX/dt, U, t)=0$ and the extraction of the explicit form (3) may not be easy, but that is not important here. Suppose the process is in some state, $X = X_0$ with input, $U = U_0$ and consider the effects of small perturbations $X = X_0+x$, $U=U_0+u$, with $\|x\|$ and $\|u\|$ both small

$$\frac{dX}{dt} = f(X_0 + x, U_0 + u, t)$$

$$\approx f(X, U, t) + \left.\frac{\partial f}{\partial X}\right|_{(X_0, U_0, t)} x + \left.\frac{\partial f}{\partial U}\right|_{(X_0, U_0, t)} u \tag{4}$$

where quadratic and higher-order terms in x, u have been neglected. The expressions $\partial f / \partial X\,|_{(X0,\, U0,\, t)}$ and $\partial f / \partial U|_{(X0, U0,\, t)}$ denote matrices of partial derivatives, evaluated at (X_0, U_0, t). Denote these Jacobian matrices by A_c and B_c, respectively. Since $X = X_0 + x$ and X_0 is a particular value of X, we have $dX/dt = dx/dt$. Hence we have the linearized model

$$\frac{dx}{dt} = A_c x + B_c u + f(x_0, U_0, t) \tag{5}$$

If (X_0, U_0) is an equilibrium point, that is, a possible steady state at time$t$, namely if, $f(X_0, U_0, t) = 0$ then clearly this model simplifies further, to the familiar from of continuous-time linear state-space model used very widely in system and control theory, namely

$$\frac{dx}{dt} = A_c x + B_c u \tag{6}$$

The outputs of a real plant are also determined from the state in a nonlinear way

$$Y = g(X, t)$$

where g is some nonlinear function and we have assumed no explicit dependence on the input U. Proceeding as before, suppose that $Y_0 = g(X_0, t)$ and $Y = Y_0 + y$. Then

$$\begin{aligned} Y &= g(X_0 + x, t) \\ &\approx g(X_0, t) + \left.\frac{\partial g}{\partial x}\right|_{(X_0,\, t)} x = Y_0 + C_y x \end{aligned} \tag{7}$$

Since we use discrete time controllers, we want to have a discrete time plant so the next step is to discretize the system (6), (7) and here, for simplicity, we use a first order Euler approximation [7]. The discretized system can be expressed as

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= C_y x + Y_0 \end{aligned} \tag{8}$$

where $A = I + T_e Ac$, $B = Te\, B_c$. (T_e Sampling Time)

3. T–S FUZZY SYSTEM (TSFS) MODELING

The set of affine systems derived above can be used to construct a TSFS [7] that approximates the nonlinear system (2) as a convex combination of the set of affine systems. This can be performed by assigning a weighting to each of the affine systems based on the certainty that each model is valid. Let ρ_i be the certainty that the i^{th} affine model is accurate, where ρ_i is defined in such a way that $\Sigma_{i=1}^{p} \rho_i = 1$ so that at each $(y, u) \in R \times R^m$. We are perfectly certain that it can be represented by the set of models that are "on" (i.e., the set $\{i: \rho_i > 0\}$). The following dynamic global fuzzy model and the definition of ρ_i the contribution of the *ith* affine system in constructing the TSFS can be expressed as:

$$\rho_i\, y(k+1) = \rho_i\, (a_1^i y(k) + \ldots + a_{na}^i y(k - na + 1) + b_1^i u(k) + \ldots + b_{nb}^i u\,(k - n_b + 1))$$

$$\sum_{i=1}^{p} \rho_i y(k+1) = \sum_{i=1}^{p} \rho_i (a_1^i y(k) + \cdots + a_{na}^i y(k - na + 1)) + \sum_{i=1}^{p} \rho_i (b_1^i u(k) + \cdots + b_{nb}^i u(k - n_b + 1)) \tag{9}$$

From the definition of ρ_i we know that

$$y(k+1) = \sum_{i=1}^{p} \rho_i (a_1^i y(k) + \cdots + a_{na}^i y(k - na + 1)) + \sum_{i=1}^{p} \rho_i (b_1^i u(k) + \cdots + b_{nb}^i u(k - n_b + 1))$$

Then, the overall TSFS can be expressed as

$$y(k+1) = a_1 y(k) + \ldots + a_{na} y(k - na + 1) + b_1 u(k) + \ldots + b_{nb} u\,(k - n_b + 1) \tag{10}$$

where, $a_j = \sum_{i=1}^{p} \rho_i\, a_j^i\; b_j = \sum_{i=1}^{p} \rho_i\, b_j^i$.

4. BRIEF INTRODUCTION TO GPC

The GPC algorithm was proposed by Clark et al. [8] and has been implemented together with other prediction control strategies in many industrial applications. In classical representation one supposes that a model of the linear (or linearized plant) is given in the following autoregressive moving average form with exogenous inputs:

$$A(z^{-1})\Delta(z^{-1})y(t) = B(z^{-1})\Delta(z^{-1})u(t^{-1})+C(z^{-1})e(t) \quad (11)$$

where $u(t)$, $y(t)$ and $e(t)$ are the input signal, output signal and disturbance process respectively, at time t, $A(z^{-1})$, $B(z^{-1})$, $C(z^{-1})$ are polynomials in the unit delay operator z^{-1} with A and C monic. The role of the Δ operator ($\Delta = 1 - z^{-1}$) is to ensure integral action of the controller in order to cancel the effect of step varying output disturbances. The GPC algorithm consists in applying a control sequence to minimize the following multistage cost function defined as follows:

$$J(u,t) = \sum_{j=N1}^{N_2} [y(t+j) - r(t+j)]^2 + \lambda \sum_{j=1}^{Nu} [\Delta u(t+j-1)]^2 \quad (12)$$

Subject to $\Delta u(t+j) = 0, j \geq N_u$ In this expression, $r(t+j)$ describes the future reference trajectory, N_2 is called the prediction horizon, $N_u \leq N_2$ is the control horizon, λ is a parameter which weights the relative importance of control effort with respect to output error. The GPC strategy may appear at first sight as an open loop control policy, since N_u future control increments are computed explicitly through the minimization of (12). However at time t one solves this optimization problem with criterion $J(u, t)$ for control strategy $\{\Delta u(t+j)\, j = 1, \ldots, N_u - 1\}$ but one applies only the first element:

$$u(t) = u(t-1) + \Delta u(t) \quad (13)$$

The control optimization process is carried over again at time t+1 with the criterion $J(u, t+1)$. This is called a receding horizon control strategy.

5. ADAPTIVE CONTROL DESIGN

For the purpose of application of parameter estimation techniques, equation (10) can be re-formulated in the following form [9], [10]:

Define

$$\begin{aligned} \varphi_1 &= [\rho_i y(k), \ldots, \rho_i y(t - n_a + 1), r_i u(t-1), \cdots, p_i u(t - n_b + 1)]^T \\ \theta_i &= [a^i_1, \ldots, a^i_{na}, \ldots, b^i_1, \ldots b^i_{nb}]^T \\ \Phi &= [\varphi^T_1, \ldots, \varphi^T_p]^T \\ \theta &= [\theta^T_1, \ldots, \theta^T_p]^T \end{aligned}$$

Then the plant (10) can be rewritten as

$$y(k+i) = \theta^T \Phi. \quad (14)$$

where φ is the regressor vector, and θ is the parameter vector. If should be noted that the plant (14) is in general nonlinear but it is linear with respect to its unknown parameters. Therefore, all the parameter adaptation algorithms developed for linear plants can be employed for the estimation of the unknown parameters in (14). It should be stressed that in most circumstances the standard recursive least squares (RLS) [11], [12] is used.

We make the following standard assumptions [13], [14]

(A1) The time delay and the plant order n_a are known.

(A2) The plant is minimum phase.

For the modeling uncertainties, we assume only:

(A3) There exists a function $\gamma(t)$ such that [15]

$$|\eta(t)|^2 \leq \gamma\ (t)$$

$\eta(t)$ represents the class of unmodelled dynamics and bounded disturbances where $\psi(t)$ satisfies

$$\psi(t) \leq \varepsilon_1 \sup_{0 \leq \tau \leq t} \|x(\tau)\|^2 + \varepsilon_2$$

for some unknown constants $\varepsilon_1 > 0$, $\varepsilon_2 > 0$, and $x(t)$ is defined as

$$x(t) = [y(t-1),\ldots, y(t-n_a), u(t-1),\ldots, u(t-n_b-1)]^T$$

6. ROBUST ADAPTIVE CONTROL WITH DEAD ZONE

Let $\hat{\theta}$ denote the estimate of the unknown parameter θ for the plant model (14). Defining the dead zone function as:

$$f(g,e) = \begin{cases} e-g & \text{if } e > g \\ 0 & \text{if } |e| \leq g \quad 0 < g < \infty \\ e+g & \text{if } e < -g \end{cases} \tag{15}$$

Then the following least squares algorithm with a relative dead zone cane be used for parameter estimation:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + a(t)P(t)\Phi(t)\overline{e}(t)^T$$

$$P(t) = P\ (t-1) - a(t)\ \frac{P(t-1)\Phi(t)\Phi(t)'P(t-1)}{1+\Phi(t)'P(t-1)\Phi(t)} \tag{16}$$

and the parameter estimate is then corrected [12] as

$$\overline{e}(t) = y(t) - \overline{\theta}(t-1)^T\ \Phi(t) \tag{17}$$

where

$$\hat{\theta}(t) = \hat{\theta}(t) + P(t)\beta(t)$$

the vector $\beta(t)$ is described in Fig.VI.1:

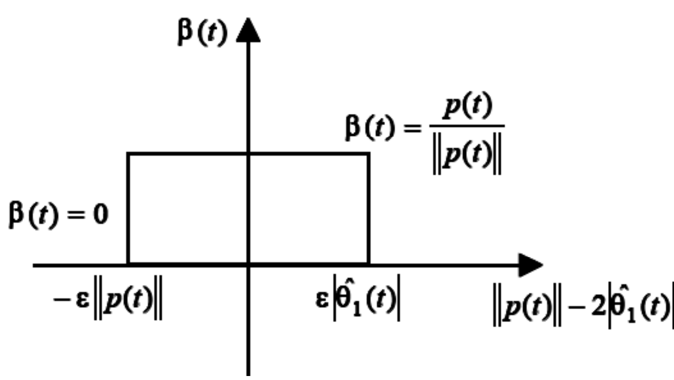

Figure 1 : Parameter Correction Vector

where $p(t)$ is the first column of the covariance matrix $P(t)$, and the term $a(t)$ is a dead zone defined as follows:

$$a(t)=\begin{cases}0 & \text{if } \left|e(t)\right|^2 \le \zeta(\hat{\gamma}(t)+Q(t)) \\ \alpha\, f(\zeta^{1/2}(\hat{\gamma}(t)+Q(t))^{1/2},\overline{e}(t))/\overline{e}(t) & \text{otherwise}\end{cases}$$

with $0<\alpha<1,\ \zeta=\dfrac{2\zeta_0}{1-\alpha},\varsigma_0>1,$ and

$$Q(t)=\left[\beta(t-1)^T P(t-1)\Phi(t)\right]^2+\frac{\alpha\mu}{2(1-\alpha)(1+\Phi(t)^T P(t-1)\Phi(t))}\times\begin{bmatrix}\sup\limits_{0\le\tau\le t}\left\|x(\tau)\right\|^2\\ 1\end{bmatrix}^T\begin{bmatrix}\sup\limits_{0\le\tau\le t}\left\|x(\tau)\right\|^2\\ 1\end{bmatrix}$$

And $\hat{\gamma}(t)$ is calculated by

$$\hat{\gamma}(t)=\hat{C}(t)^T\begin{bmatrix}\sup\limits_{0\le\tau\le 0}\left\|x(\tau)\right\|^2\\ 1\end{bmatrix} \tag{18}$$

$$\hat{C}(t)=\hat{C}(t-1)+\frac{a(t)\mu}{(1-\alpha)(1+\Phi(t)^T P(t-1)\Phi(t))}\times\begin{bmatrix}\sup\limits_{0\le\tau\le t}\left\|x(\tau)\right\|^2\\ 1\end{bmatrix}$$

$$\mu>0 \tag{19}$$

where $\hat{C}(t)^T] = [\hat{\varepsilon}_1\,\hat{\varepsilon}_2]$

with zero initial condition. It should be noted that $\hat{\varepsilon}_1$ and $\hat{\varepsilon}_2$ will be always positive and non-decreasing.

Remark: The prediction error $\overline{e}(t)$ is used in the modified least squares algorithm to ensure that the estimator property (iii) in the following lemma can be established. The properties of the above modified least squares parameter estimator are summarized in the following lemma.

Lemma: The least squares algorithm (16)-(19) has the following properties [16]:

(i) $\hat{\theta}(t)$ is bounded, and $\|\hat{\theta}(t)-\hat{\theta}(t-1)\|\in I_2$.

(ii) $\hat{C}(t)$ is bounded and non-decreasing, thus converges.

(iii) $\dfrac{f(\zeta^{1/2}\gamma(t)^{1/2},\overline{e}(t))^2}{1+\Phi(t)^T P(t-1)\Phi(t)}\in l_2$

(iv) $\left\|p(t)\right\|+\left|\hat{\theta}^1(t)\right|>b_{\min}$ where $b_{\min}=\dfrac{\left|\theta^1\right|}{\max\left(1,\left\|\beta^*\right\|\right)}$

with β^* defined such that

$\theta^* = \hat{\theta}(t) = P(t)\,\beta^*$

(v) $\left|\bar{\theta}^1(t)\right| > \frac{1-\varepsilon}{3+\varepsilon} b_{\min}$.

(vi) $\bar{\theta}(t)$ bounded, and $\|\bar{\theta}(t) - \bar{\theta}(t-1)\| \in l_2$.

Proof : Define a Lyapunov function candidate

$$V(t+1) = \frac{1}{2}(\tilde{\theta}(t)^T P(t)^{-1}\tilde{\theta}(t) + C(t+1)^T \mu^{-1}\tilde{C}(t+1))\mu \tag{20}$$

where $\tilde{\theta}(t) = \tilde{\theta}(t) - \theta^*, \tilde{C}(t+1) = \hat{C}(t+1) - [\varepsilon_1 \quad \varepsilon_2]$. Noting that

$$\begin{aligned}\bar{e}(t) &= y(t) - \bar{\theta}(t-1)^T \Phi(t)\\ &= y(t) - \hat{\theta}(t-1)\,\Phi(t)\,\beta(t-1)^T P(t-1)\,\Phi(t)\\ &= e(t) - \beta(t-1)^T P(t-1)\,\Phi(t)\end{aligned} \tag{21}$$

Then, the difference of the Lyapunov function candidate becomes

$$V(t+1) - V(t) = \frac{a(t)}{1+\Phi(t)^T P(t-1)\Phi(t)} \times \left[\frac{1+\Phi(t)^T P(t-1)\Phi(t)}{1+\big(1-a(t)\big)\Phi(t)^T P(t-1)\Phi(t)} \times \Big(\eta(t) - \beta(t-1)^T P(t-1)\Phi(t)\Big)^2 - \bar{e}(t)^2\right]$$

$$+\frac{a(t)\tilde{C}(t)^T}{(1-\alpha)\Big(1+\Phi(t)^T P(t-1)\Phi(t)\Big)}\begin{bmatrix}\sup\limits_{0\le\tau\le t}\|x(\tau)\|^2\\ 1\end{bmatrix} + \frac{a(t)^2\mu}{(1-\alpha)^2\Big(1+\Phi(t)^T P(t-1)\Phi(t)\Big)^2}\begin{bmatrix}\sup\limits_{0\le\tau\le t}\|x(\tau)\|^2\\ 1\end{bmatrix}^T\begin{bmatrix}\sup\limits_{0\le\tau\le t}\|x(\tau)\|^2\\ 1\end{bmatrix}$$

$$\le \frac{a(t)}{1+\Phi(t)^T P(t-1)\Phi(t)} \times \left[\frac{1}{1-\alpha}\Big(\eta(t) - \beta(t-1)^T P(t-1)\Phi(t)\Big)^2 - \bar{e}(t)^2\right] + \frac{2a(t)\big(\hat{\gamma}(t)-\gamma(t)\big)}{(1-\alpha)\Big(1+\Phi(t)^T P(t-1)\Phi(t)\Big)}$$

$$+\frac{a(t)^2\mu}{(1-\alpha)^2\Big(1+\Phi(t)^T P(t-1)\Phi(t)\Big)^2}\begin{bmatrix}\sup\limits_{0\le\tau\le t}\|x(\tau)\|^2\\ 1\end{bmatrix}^T \times \begin{bmatrix}\sup\limits_{0\le\tau\le t}\|x(\tau)\|^2\\ 1\end{bmatrix}$$

$$\le \frac{a(t)}{1+\Phi(t)^T P(t-1)\Phi(t)} \times \left[\frac{2}{1-\alpha}\eta(t)^2 - \frac{2}{1-\alpha}\Big(\beta(t-1)^T P(t-1)\Phi(t)\Big)^2 - \bar{e}(t)^2\right]$$

$$+\frac{2a(t)\big(\hat{\gamma}(t)-\gamma(t)\big)}{(1-\alpha)\Big(1+\Phi(t)^T P(t-1)\Phi(t)\Big)}$$

$$+\frac{a(t)^2\mu}{(1-\alpha)^2(1+\Phi(t)^T P(t-1)\Phi(t))^2}\begin{bmatrix}\sup\limits_{0\le\tau\le t}\|x(\tau)\|^2\\ 1\end{bmatrix}^T \times \begin{bmatrix}\sup\limits_{0\le\tau\le t}\|x(\tau)\|^2\\ 1\end{bmatrix}$$

$$\leq \frac{a(t)}{1+\Phi(t)^T P(t-1)\Phi(t)} \times \left[\frac{2}{1-\alpha}\eta(t)^2 - \overline{e}(t)^2 + \frac{2}{1-\alpha}\left(\hat{\gamma}(t) - \gamma(t) + Q(t)\right) \right]$$

$$\leq \frac{a(t)}{1+\Phi(t)^T P(t-1)\Phi(t)} \left[-\overline{e}(t)^2 + \frac{2}{1-\alpha}\left(\hat{\gamma}(t) + Q(t)\right) \right]$$

$$\leq \frac{a(t)}{1+\Phi(t)^T P(t-1)\Phi(t)} \left[-\overline{e}(t)^2 + \frac{2}{1-\alpha}\frac{1}{\zeta}\overline{e}(t)^2 \right]$$

$$\leq \frac{a(t)}{1+\Phi(t)^T P(t-1)\Phi(t)} \left[-\overline{e}(t)^2 + \frac{1}{\zeta_0}\overline{e}(t)^2 \right]$$

$$\leq -\frac{\zeta_0 - 1}{\zeta_0} \frac{a(t)}{1+\Phi(t)^T P(t-1)\Phi(t)} \overline{e}(t)^2$$

$$\leq -\frac{\zeta_0 - 1}{\zeta_0} \frac{f\left(\zeta^{1/2}\left(\gamma(t) + Q(t)\right)^{1/2}, \overline{e}(t)\right)^2}{1+\Phi(t)^T P(t-1)\Phi(t)} \tag{22}$$

where the fact that $a(t)e(t)^2 = f(t)e(t) \geq f(t)^2$ has been used. Therefore, following the same arguments as in [17], the results (i)-(iii) in Lemma are thus proved. The properties (iv)-(vi) in the lemma can also be obtained directly from the results in [18]. If using the same adaptive control law as in equation (13), then with the properties (i)-(vi), the global stability and convergence results of the new adaptive control system can be established as in [13], [15] as long as the estimated $\overline{\varepsilon}_1$ is small enough, which are summarized in the following Theorem.

Theorem: The direct adaptive control system satisfying assumptions (A1)-(A3) with the adaptive controller described in equations (16)-(19) and (13) is globally stable in the sense that all the signals in the loop remain bounded.

7. SIMULATION RESULTS

Consider the surge tank model that can de represented by the following differential equation [4]:

$$\frac{dh(t)}{dt} = \frac{-c\sqrt{2gh(t)}}{A\left(h(t)\right)} + \frac{1}{A\left(h(t)\right)}u(t) \tag{23}$$

where $u(t)$ is the input flow (control input), which can be positive or negative, $h(t)$ is the liquid level (output of the system); $A(h(t))$ is the cross-sectional area of the tank; $g = 9.8\text{m/sec}^2$ is gravity; and $c = 1$ is the known cross-sectional area of the output pipe. Let $A(h(t)) = ah^2 + b$, where $a = 1$ and $b = 2$. Using Euler approximation to discretize the system, we have

$$h(k+1) = \max\left\{0.001, h(k) + T\left[\frac{-\sqrt{19.6h(k)}}{A(h(k))} + \frac{u(k)}{A\left(h(k)\right)}\right]\right\} \tag{24}$$

where $T = 0.1$, and $\max\{0.001, .\}$ is used to ensure that the liquid level never goes negative. The number of affine systems used here is $p = 15$.

Robust Adaptive Fuzzy Model Predictive Control is applied to the tank example where a random white noise of zero mean and 0.2 variance is added to the output before it is fed back.

The parameters of the dead zone which are: $Q(t)$, $\hat{C}(t)$. $\hat{\gamma}(t)$ calculated on line in a hierarchical way, with the updated rate parameters $\mu = 1.7^{*}10^{-5}$.

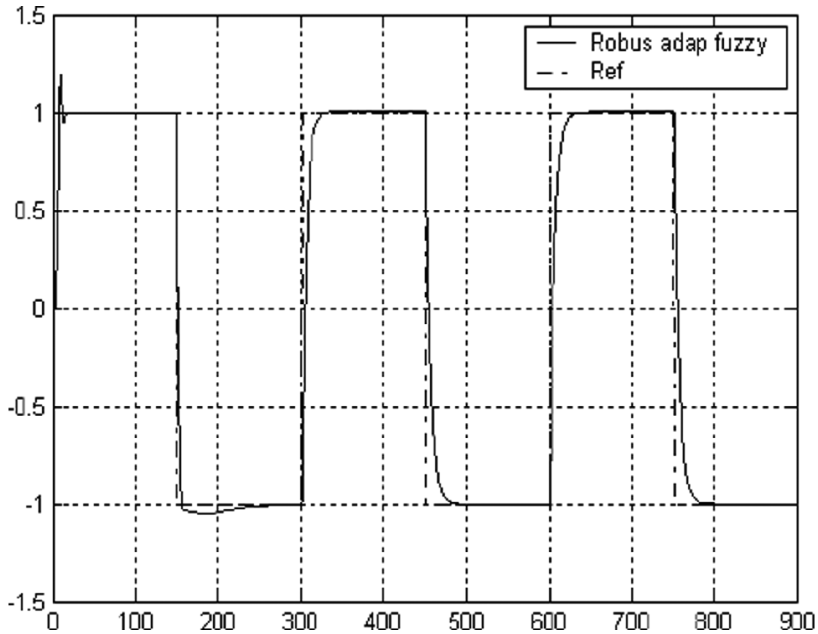

Figure 2: Output Signal

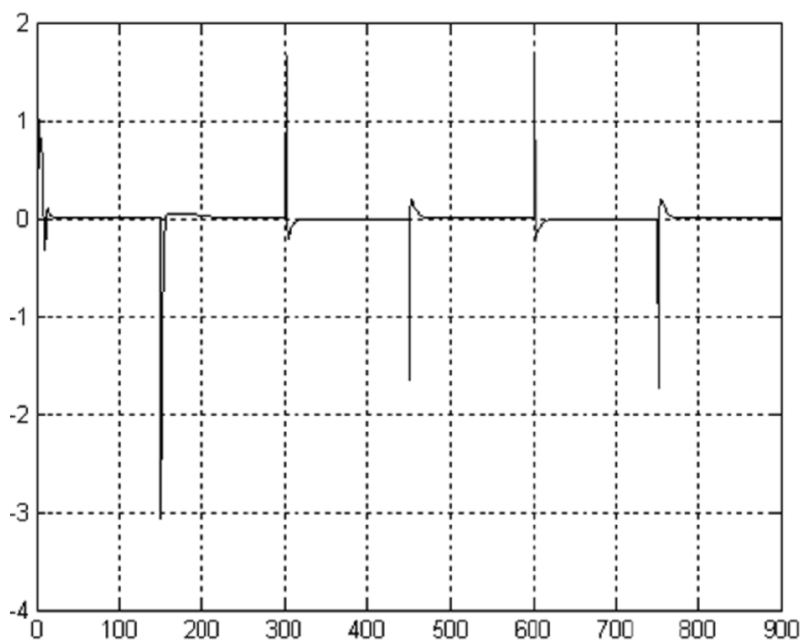

Figure 3: Control Signal

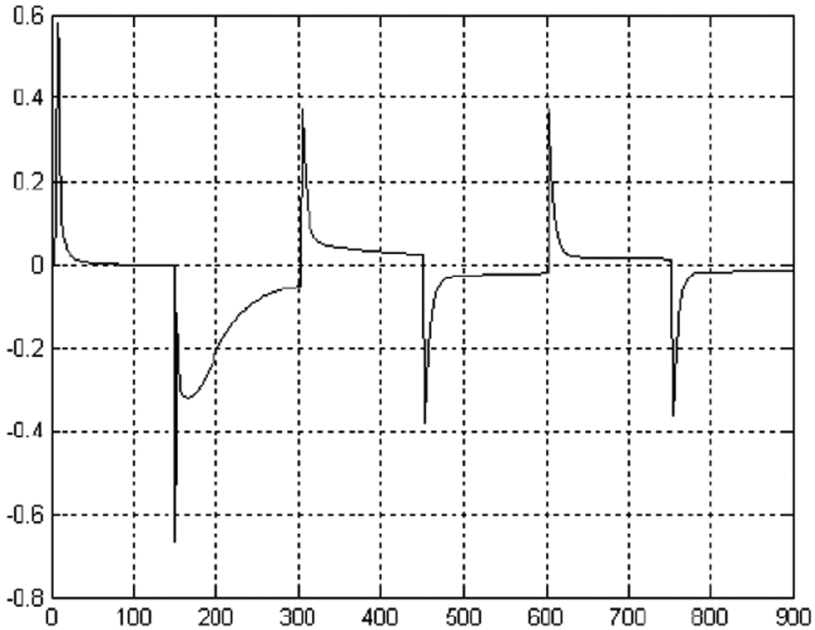

Figure 4: Error Signal

I can be observed from the above simulation results that the algorithm developed in this chapter can guaranteed the stability of the fuzzy adaptive system in the presence of the noise and smaller tracking error. We notice that the response of the system with less overshoot and with faster convergence.

8. CONCLUSION

This paper present a general scheme for computing robust adaptive FMPC is a model-based control scheme, closed-loop performance is expected to be improved by improving the accuracy of the model. Therefore there is a need to update the parameters of the TSFS online so that it becomes a more accurate approximation of the actual system. The TSFS used here is a convex combination of multiple affine systems whose parameters can be updated online using standard update routines such as recursive least squares (RLS). Here, RLS is used to update the parameters of all affine models online. The final TSFS becomes an interpolation between multiple affine time-varying models. The effectiveness of this approach was demonstrated through a simulated example of a surge tank system.

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