'93 KACC (1993. 10. 20~22)

Intelligent Adaptive Controller for a Process Control

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Abstract

In this paper, an intelligent adaptive controller is proposed for the process with unmodelled dynamics. The intelligent adaptive controller consists of the numeric adaptive controller and the intelligent tuning part. The continuous scheme is used for the numeric adaptive controller to avoid the problems occurred in the discrete time schemes. The adaptive controller is adopted to the process with time delay. It is an implicit adaptive algorithm based on GMV using the emulator.

The tuning part changes the design parameters in the control algorithm. It is a multilayer neural network trained by robustness analysis data. The proposed method can improve the robustness of the adaptive control system because the design parameters are tuned according to the operating points of the process.

Through the simulation, robustnesses are shown for intelligent adaptive controller. Finally, the proposed algorithms are implemented on the electric furnace temperature control system. The effectiveness of the proposed algorithm is shown from experiments.

1. Introduction

Recently, research on adaptive control has focused on guaranteeing global stability and robustness on plant dynamics uncertainties or variations.

Robustness analysis of the adpative control is discussed lively on early 1980's. Narendra[1], Morse[2], Egardt[3], and Goodwin[4] demonstrated stability of the adaptive control for some assumptions —upper bound of system order, relative degree, magnitude of high frequency gain of process transfer function, nonminimum phase system, time invariant and no disturbance. Further, Narendra[5], Goodwin[6], and Samson[7] proved stablility to system with finite disturbance.

However, Adaptive control may have the weakness for practical application when it doesn't consider uncertainties of plant model. Athans[8] detected problem of feedback loop system with unmodelled dynamics. Rohr[9] indicated that control input includes the frequency exciting high frequency unmodelled component if there exist unmodelled dynamics and noise component in the system. For solving problems of model uncertainty, many reseachers have investigated roubustness in the view of the practical issue. Anderson and Johnson[10] showed robustness according to variant parameter when controller is satisfied with PE(Persisterntly Excitation) condition by analysing response. Ortega[11] designed controller which is able to solve unmodelled dynamics problem by adjusting observer pole of indirect adaptive controller. Adaptive controller which is satisfied with local stability is designed by Kosut, who introduced SGT(Small Gain Theorem)[12]. Also, Gawthrop and Lim[13] applied SGT to self tuning regulator in order to satisfy stability range. Likewise, many researchers have studied in order to improve robustness of plant under uncertainties.

In this paper, we design the intelligent adaptive controller for the process. The proposed controller includes neural network tuning part in order to improve robustness. Artificial neural nertworks can be have applied sucessfully in various field and a good approximation to the nonlinearity. For improving robustness, we introduce the control weighting parameter guaranteeing stable response. In control, it is tuned by neural network. The numerical adaptive controller algorithm is GMV and is designed in continuous domain for reducing some problems (sampling period, nonminimun phase, time delay)

2. Hybrid Adpative Controller

Consider SISO(Single Input Single Output) plant with time delay.

$$y(s) = e^{-sT}\frac{B(s)}{A(s)}u(s) + \frac{C(s)}{A(s)}v(s) \quad (1)$$

where $u(s)$ is plant input, $y(s)$ is plant output, $v(s)$ is disturbance, T is time delay, and

$$A(s) = a_n s^n + a_{n-1}s^{n-1} + \cdots + a_0 \quad (2)$$

$$B(s) = b_m s^m + b_{m-1}s^{m-1} + \cdots + m_0 \quad (3)$$

$$C(s) = c_k s^k + c_{k-1}s^{k-1} + \cdots + c_0 \quad (4)$$

It needs emulator in order to compensate time delay of system. Emulator is also able to compensate unstable zero, relative degree larger than zero. Emulator is following,

$$\phi(s) = s^{sT} \frac{P(s)}{Z(s)} y(s) \tag{5}$$

where e^{sT} is predictor, $P(s)$ is differentiator, $Z(S)$ is zero-cancellation compensator. For implementaion, exponential function is approximated by pade approximation method

$$e^{sT} \approx \frac{D(s)}{D(-s)} \tag{6}$$

where $D(s) = d_n s^n + d_{n-1} s^{n-1} + \cdots + d_1 s + 1$

The Emulator can be rewritten by substituting (6) into (5)

$$\begin{aligned}\phi(s) &= e^{sT} \frac{P(s)}{Z(s)} y(s) \\ &= \frac{P(s)}{Z(s)} \frac{B(s)}{A(s)} u(s) + \frac{D(s)}{D(-s)} \frac{P(s)}{Z(s)} \frac{C(s)}{A(s)} v(s)\end{aligned} \tag{7}$$

In (7), second term is seperated by $Z(s) = Z^+(s)Z^-(s)$, $Z^+(s)$ has the root in LHP(Left Half Plane) and $Z^-(s)$ has the root in RHP(Right Half Plane). It represents following diophantine equation for seperating two terms.

$$\frac{D(s)P(s)C(s)}{D(-s)Z(s)A(s)} = \frac{E(s)}{D(-s)Z^-(s)} + \frac{F(s)}{Z^+(s)A(s)} \tag{8}$$

where $E(s)$, $F(s)$ are unknown polynomials and are obtained by solving diophantine equation. Now, subsituting (8) into (7) gives

$$\begin{aligned}\phi(s) &= \left[\frac{P(s)B(s)}{Z(s)A(s)} u(s) + \frac{F(s)}{Z^+(s)A(s)}\right] v(s) + \frac{E(s)}{D(-s)Z^-(s)} v(s) \\ &= \phi^*(s) + e^*(s)\end{aligned} \tag{9}$$

where $\phi^*(s)$ is able to implement and $e^*(s)$ is implementation error.

$$\begin{aligned}\phi^*(s) &= \frac{P(s)B(s)}{Z(s)A(s)} u(s) + \frac{F(s)}{Z^+(s)C(s)} y(s) - \frac{F(s)D(-s)B(s)}{Z^+(s)A(s)D(s)C(s)} u(s) \\ &= \frac{F(s)}{Z^+(s)C(s)} y(s) + \frac{E(s)B(s)}{T(s)C(s)Z^-(s)} u(s) \\ &= \phi_y^*(s) + \phi_u^*(s)\end{aligned} \tag{10}$$

Control input is generated by the following equation and overall feedback control system is illustrated in fig. 1.

$$u(s) = \frac{1}{Q(s)} [w(s) - \phi^*(s)] \tag{11}$$

$$Q(s) = \frac{qs}{Q_d(s)} \tag{12}$$

Control weighting transfer function $Q(s)$ is used in order to improve robustness of system.

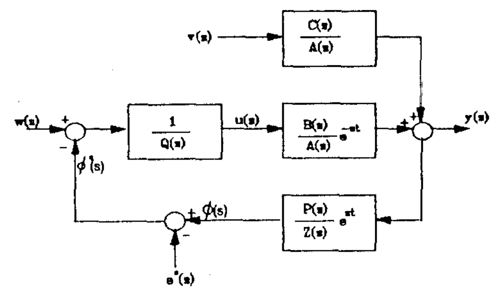


Fig. 1. Feedback Control System

From fig. 1, loop gain ($L(s)$) and feedback transfer function is obtained as following

$$y(s) = e^{-sT} \frac{L(s)}{1+L(s)} \frac{Z(s)}{P(s)} [w(s) + e^*(s)] + \frac{1}{1+L(s)} \frac{C(s)}{A(s)} v(s) \tag{13}$$

$$u(s) = \frac{1}{1+L(s)} \frac{1}{Q(s)} [w(s) - e^{sT} \frac{C(s)P(s)}{A(s)Z(s)} V(s) + e^*(s)] \tag{14}$$

$$L(s) = \frac{1}{Q(s)} \frac{B(s)}{A(s)} \frac{P(s)}{Z(s)} \tag{15}$$

Eq. (13), (14) are feedback transfer functions to output, input. Loop gain is represented in (15). From (14) and (15), time delay factor dosen't influence to the denominator of charateristic polynomial $1+L(s)$. That is, ideal stabililty of feedback system doesn't relate to time delay. As $Q(s)$ is close to zero, transfer function to reference input is $Z(s)/P(s)$. This paper assume following condition so that it has detuned MRAC.

$$Z^+(s) = 1 \tag{16.a}$$

$$Z^-(s) = P(\varepsilon s); \quad 0 < \varepsilon < 1 \tag{16.b}$$

For estimating the patameters of a process, it is necessary to have estimation method that update the parameters recursively. Least squares estimation method is a basic technique for parameter estimation. System can be defined for a mathmatical model that can be written in the form

$$y(t) = \varphi(t)^T \theta \tag{17}$$

where y is system output, φ are known variables, θ are unkown parameters.
The least squares error can be written by

$$e(t) = y(t) - \hat{y}(i) = y(t) - \varphi^T(t)\theta \tag{18}$$

The cost function can be now written as

$$V(\theta, t) = \frac{1}{2} \sum_{i=1}^{t} e(i)^2 = \frac{1}{2} \sum_{i=1}^{t} (y(i) - \varphi^T \theta)^2 \tag{19}$$

Assume Φ is $[\varphi^T(1) \cdots \varphi^T(t)]$. Then for obtaining the minimum cost function

$$\hat{\theta} = (\Phi^T \Phi)^{-1} \Phi^T Y \tag{20}$$

In adaptive controller, the observations are obtained sequentially in real time. It is desirable to make the computations recursively in order to save computation time.

$$\hat{\theta}(t) = (\sum_{i=1}^{t}\varphi(i)\varphi^T(i))^{-1}(\sum_{i=1}^{t}\varphi(i)y(i)) = P(t)(\sum_{i=1}^{t}\varphi(i)y(i))$$
$$= P(t)(\sum_{i=1}^{t-1}\varphi(i)y(i) + \varphi(t)y(t)) \quad (21)$$

where $\sum_{i=1}^{t-1}\varphi(i)y(i) = P(t)^{-1}\hat{\theta}(t-1) - \varphi(t)\varphi^T(t)\hat{\theta}(t-1)$

The estimate at time t can be written as

$$\hat{\theta}(t) = \hat{\theta}(t-1) - P(t)\varphi(t)\varphi^T(t)\hat{\theta}(t-1) + P(t)\varphi(t)y(t)$$
$$= \hat{\theta}(t-1) + K(t)(y(t) - \varphi^T(t)\hat{\theta}(t-1)) \quad (22)$$

where $K(t) = P(t)\varphi(t)$

The case of slowly time-varying parameters can be replaced the least squares cost function with

$$V(\theta,t) = \frac{1}{2}\lambda^{t-i}\sum_{i=1}^{t}(y(i) - \varphi^T(i)\theta)^2 \quad (23)$$

where λ is forgetting factor, $0 < \lambda \le 1$

Recursive least squares method that uses (23) is called exponential forgetting RLS(ERLS) and ERLS[14] is given by

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)(y(t) - \varphi^T(t)\hat{\theta}(t-1))$$
$$K(t) = P(t)\varphi(t) \quad (24)$$
$$P(t) = (I - K(t)\varphi^T(t))P(t-1) / \lambda$$

Direct(Implicit) adaptive controller is constructed with emulator and least square estimator. Direct adaptive controller estimates parameter of emulator directly and then designs controller. For comparing between emulator output and actual output, realizability filter is introduced. Filtered emulator $\phi_\Lambda(s)$ is following

$$\phi_\Lambda(s) = \Lambda(s)\phi(s) \quad (25)$$

$\Lambda(s)$ choose following so that $y(t) = \phi_\Lambda(t)$.

$$\Lambda(s) = e^{-sT}\frac{Z(s)}{P(s)} \quad (26)$$

Continuous adaptive controller has to convert discrete adpative one so that it works on digital computer. we call it Hybrid adaptive controller. Controller designed in continuous domain is able to overcome problems occured in discrete control — sampling period, plant zero, fractional time delay, etc al. Overall Hybrid adaptive controller consists of controller and estimator.

Discrete control input is generated by

$$u(z) = \frac{1}{Q(z)}(w(z) - \phi(z)) \quad (27)$$

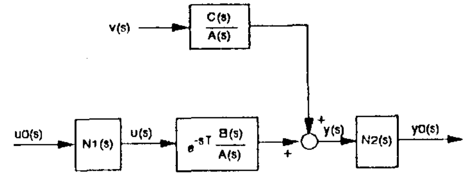


Fig 2. System with unmodelled dynamics

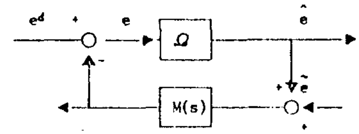


Fig 3. Error model system

For discretization, we uses following bilinear transformation

$$s = \frac{2}{T}\frac{z-1}{z+1} \quad (28)$$

Design procedure of the control system is following

Step 1) Determine the $P(s)$, $Z(s)$, $C(s)$, $Q(s)$

Step 2) Determine the plant order and sampling period

Step 3) Build the discrete predictor $\phi(z)$ corresponding to the continuous predictor $\Phi(s)$

Step 4) Build the discrete controller as (27)

3. Robustness Analysis

It is necessary to consider robustness of adaptive controller in order to apply the adaptive controller to the plant. For analysing robustness, assume the plant with unmodelled dynamics in presence as fig. 2.

As shown in fig. 2, both $u(s)$ and $y_0(s)$ are affected by $N_1(s)$, $N_2(s)$, repectively. Error equation of direct adpative controller can be decribed as

$$e(s) = e^{-d} - M(s)(\tilde{e}(s) + M(s)\hat{e}(s)) \quad (29)$$

where $\tilde{e}(s)$ is filter induced error, $\hat{e}(s)$ is estimation error, $e(s)$ is observation error, $e^{-d}(s)$ is disturbance and setpoint induced error.

Fig. 3 shows error model system. $M(s)$ is induced by considering unmodelled transfer function $N(s)$ in presense between output of controller and input of system and

$$M(s) = \frac{Z^*(s)E(s)A(s)}{P(s)C(s)}\frac{N^{-1}(s)-1}{1+L^{-1}(s)N(s)} \quad (30)$$

$$N(s) = \frac{A_n(s)}{B_n(s)} \quad (31)$$

From fig. 3, Ω is transfer function of estimation system. In order to stablilize the system with unmodelled dynamics by small gain theorem[13], it is satisfied with following conditions.

Assumption 1) $N(s)$ is stable

Assumption 2) $G(s)$ is stable

$$G(s) = \frac{L(s)}{1+L(s)N(s)}$$

Assumption 3) gain of $M(s)$ is less than 1

From (13), (30), and (31), $M(s)$, $L(s)N(s)$ is given as

$$M(s)=\frac{B(s)E(s)Q_d(s)A(s)Z^*(s)[A_N(s)-B_N(s)]}{D(s)C(s)[qsA(s)Z(s)A_N(s)+Q_d(s)B(s)P(s)B_N(s)]} \quad (32)$$

$$L(s)N(s) = \frac{Q_d(s)B(s)P(s)B_N(s)}{qsA(s)Z(s)A_N(s)} \quad (33)$$

Now, it illustrates procedure of choosing the control weighting parameter in order to stabilize the plant under the unmodelled dynamics. First, Identify whether unmodelled dynamics $N(s)$ is stable. Second, choose the stable polynomial, $P(s)$, $C(s)$ and find weighting value q stablizing $G(s)$. Here, limitation of q is defined in Root-Locus of open-loop transfer function $L(s)N(s)$ including unmodelled component. Third, apply q to $M(s)$ and identify whether magnitude of $M(s)$ is less than 1 from Nyquist plot and Bode plot. Finally, untill get the range of q satisfying the stable condition, repeat the procedure.

4. Intelligent tuning of Adaptive Controller

Intelligent adaptive controller is shown in fig. 4. It consists of two part, control parameter tuning part and direct adpative control part. The tuning part is built by using multilayered neural networks. For determining the q, inputs of neural network use output error, derivative output error of plant. As showing the table 1, approriate q is selected by the time response of plant.

Table 1. Normalization data for parameter q

e	1	0.5	0	0	0	0.5	1	1
de	1	1	1	0.5	0	0	0	0.5
q	0	0.5	1	0.5	1	0.5	0.5	0.5

Overall structure of intelligent adaptive controller is following fig. 4.

5. Case study and Simulation Results

In this section, we analysis robustness of plant with unmodelled dynamics and simulate adaptive controller with fixed q and proposed intelligent adaptive controller.

Example) Set the control weighting parameter for robustness.

Assume the plant with first order time delay, unmodelled component is second order system.

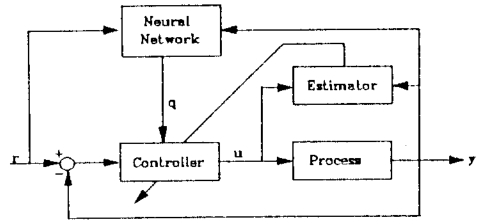


Fig. 4. Intelligent Adaptive Control system

$$\frac{B(s)}{A(s)} = \frac{1}{10s+1}e^{-sT} \quad (34)$$

$$N(s) = \frac{100}{s^2+8s+100} \quad (35)$$

Set the parameter q in case T=1, T=3 and $P(s)$, $C(s)$, $Z(s)$ is given following

$$P(s) = C(s) = s + 0.01 \quad (36)$$

$$Z(s) = 0.1s + 0.01 \quad (37)$$

First, determine the lower bound of q from Root-Locus. In fig. 5, when q is 0.052, it locates on the boundary of unstable region and it can be located on the stable region by bigger q. Next, as above condition, range of q is known by Nyquist plot of $M(s)$ and is shown in fig. 6. Also, because time delay factor affects the maginitude of $M(s)$, q is needed to be adjusted. That is, for getting the $M(s)$ less than 1, we have to take large q. This results is illustrated in fig. 7.

5.1 Roubustness of plant with time delay

Now, we investigate robustness to the system with time delay including unmodelled dynamics. Consider following simulation model

$$G(s) = \frac{2}{(s+1)}e^{-2s} \quad (38)$$

unmodelled dynamics and design polynomial is following

$$N_{pz}(s) = \frac{5}{s^2+5s+5} \quad (39)$$

$$N_d(s) = e^{-3s} \quad (40)$$

$$P(s) = C(s) = 1 + 0.3s\ , \quad z(s) = 1 + 0.03s \quad (41)$$

For control weighting value q, use to the procedure in section 4. Because the effect of time delay does not present in Root Locus, q is determined in Nyquist plot about $M(s)$. Fig. 8(a) shows the result of unmodelled dynamics about pole-zero in Nyquist plot. The effect of unmodelled time delay in Nyquist plot is illustrated in fig. 8(b). As showing the Nyquist plot, we know that q is large for unmodelled dynamics. Time response about q is shown in fig. 9(a)(b).

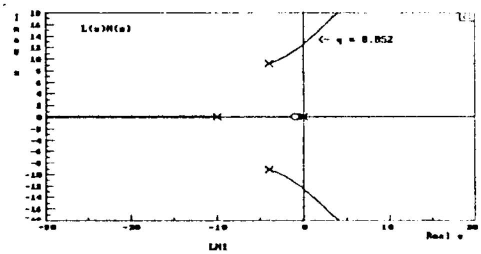
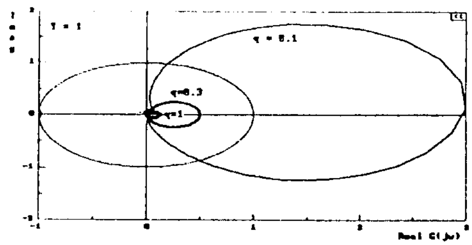
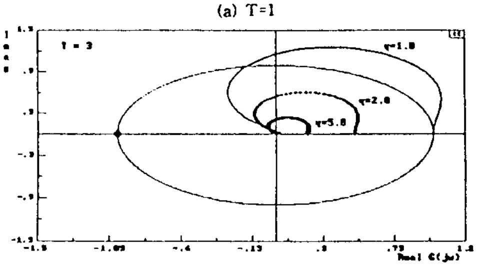


Fig. 5. Root-Locus of $L(s)N(s)$

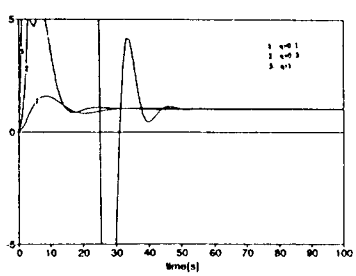


(a) T=1

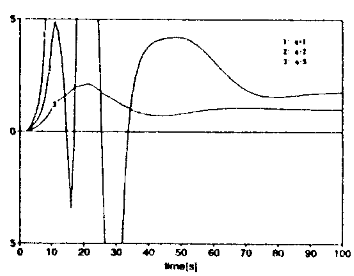


(b) T=3

Fig. 6. Nyquist plot of $M(s)$

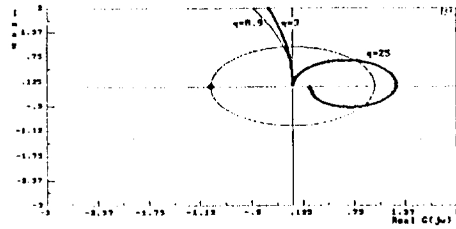


(a) T=1

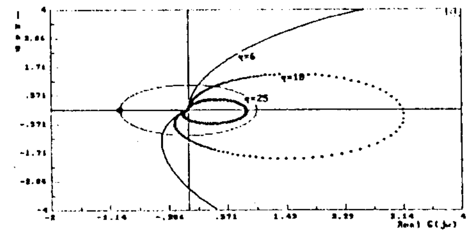


(b) T=3

Fig. 7. Time response about q

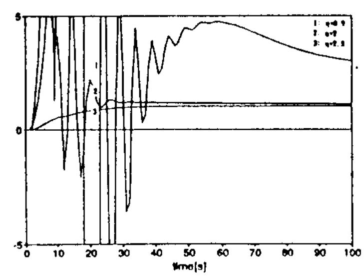


(a) N_{pz}

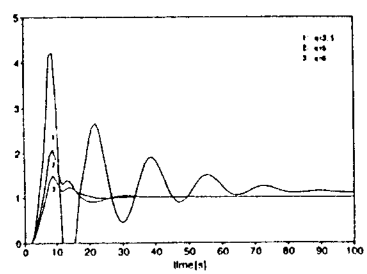


(b) N_d

Fig. 8. Nyquist plot of the plant with time delay for unmodelled dynamics



(a) N_{pz}



(b) N_d

Fig. 9. Time response

5.2 Comparison intelligent adaptive controller and fixed q paramter adaptive controller

Consider the plant with time delay and unmodelled dynamics

$$G(s) = \frac{5}{50s+1} e^{-2s} \tag{42}$$

$$N_{pz1}(s) = \frac{30}{s^2+10s+30} \tag{43}$$

$$N_{pz2}(s) = \frac{0.01}{s^2+0.02s+0.01} \tag{44}$$

we choose large q which is 50 for considering robustness. Sampling time is 1 second for discretization. Simulation results is shown in fig. 10 and fig. 11

From fig. 10, as unmodelled pole is close to zero, it shows initial large overshoot and unstable steady state .

From fig. 11, even unmodelled pole is close to zero, it improves overshoot and unstable steady state. For tuning the parameter, trainig rate of neural network is 0.9 and the number of neuron per layer are 2, 6, 1.

6. Experiment results.

Now, we assess the proposed intelligent adaptive algorithm through applying electric furnace system. The configuration of electric furnace control system is illustrated in fig. 12.

Electric furnace control system consists of five part, Electric furnace process, IBM-PC, sensor part, PWM generator, PIO(programmable input output) interface part. First, for comparision, PI controller is applied to the electric furnace and sampling period 10 seconds. Fig. 13 shows the result of PI control to the electric furnace.

The parameter of PI controller is adjusted by Ziegler-Nichols tuning method. Each parameter is set to K=1.912, Ti=1152.

Now, apply proposed Intelligent adaptive control to the electric furnace in fig. 14. In comparision, it improves overshoot than PI control. Further, if neural network is sufficiently trained, control weight q is set more approriate to the variable operating point.

7. Conclusion

This paper proposed intelligent adpative controller for effective control the process. It includes direct adaptive controller considering plant with time delay and investigates robustness to the unmodelled dynamics. Intelligent adaptive controller contains on-line tuning part using multilayered neural network for improving robustness of plant with unmodelled dynamics. Through the simulation and experiment, we conclude the following.

1) Analysis the robustness to the plant including the unmodelled dynamics.
2) we know that it is needed to get large q for unmodelled large time delay, high order pole-zero

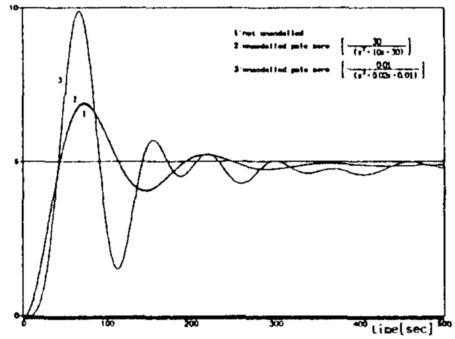


Fig. 10. Time response of the Hybrid Adaptive Controller

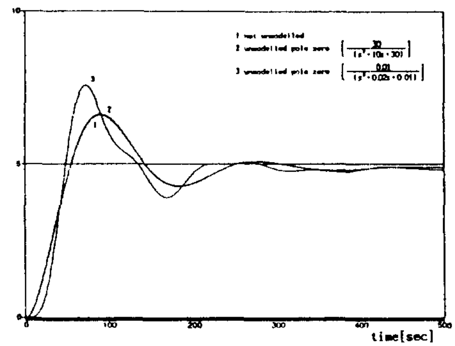


Fig. 11. Time response of the Intelligent Adaptive Controller

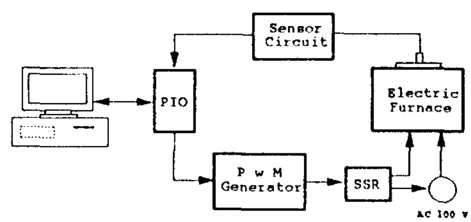


Fig. 12. Electric furnace control system

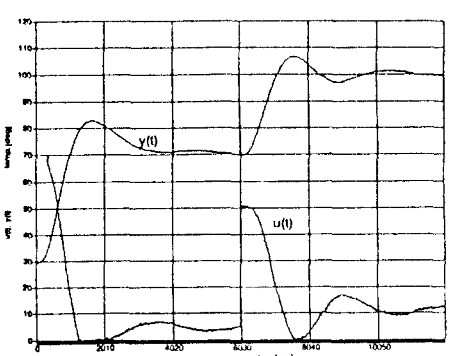


Fig. 13. PI control

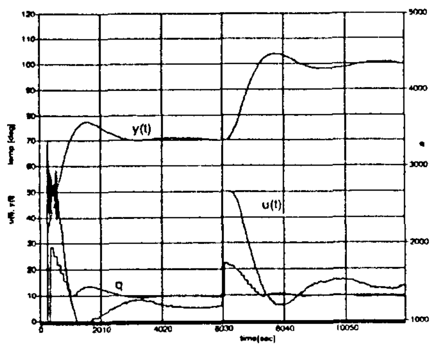


Fig. 14. Intelligent adaptive control

3) A simulation study shows that intelligent adaptive controller improves the robustness of plant. That is, as using the neural network, it is able to get the approriate control weigthing parameter q for improving the robustness of plant.
4) In experiment, Intelligent adaptive control shows better time response than PI control.

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