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# Adaptive Fuzzy Control Using Ant Colony Optimization for Unknown Systems with Time-Delay

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**Abstract:** An adaptive control method is proposed for the unknown system with time-delay in this paper. There are two main parts. First, in order to effectively control unknown systems with time-delay, Adaline network is used to on-line estimate the unknown steady-state gain and time-delay of the systems and estimated values modify parameters of Smith predictor in real-time. Next, a new method of adaptive fuzzy control using improved ant colony optimization (ACO) algorithm is proposed for controlling the unknown systems with time-delay. The ant colony algorithm is used to optimize the rules and the parameters of the fuzzy controller. This method can also apply to control slow time-varying systems with time-delay. Simulation results show that the method is efficient and practical. *Copyright © 2014 FSA Publishing, S. L.*

**Keywords:** Smith predictor, parameters estimation, ant colony optimization, fuzzy control, Adaline network.

## 1. Introduction

There are many the slow varying with time and the unknown systems with time-delay in industry. Delays may be cause systems to destabilize or degrade their feedback performance. When production condition or demand of plants is changed, many systems are often accompanied by parameters slow varying with time and uncertainty. It is very difficult to control such delay systems.

Many different approaches have been developed to control such systems. A number of systems utilize traditional control methods, i.e., proportional–integral or proportional–integral–derivative controller based on the classical unity feedback closed loop structure for the unknown systems with time-delay. Generally, these methods are able to provide good control system performance when the pure time-delay of such systems is negligible or small, but their control effect is often poor when time-delay of the systems is large. The control scheme of Smith predictor is an effective control method for time-delay systems [1]. It makes use of an estimated model of the system to lead to an exact, but delayed, replica of the response that would have been obtained without the time-delay. Attention has been paid to this control scheme over the years [2, 3]. In Smith's scheme, a predictor is equivalent to the time-delay free part of the system. Control is applied based on feedback information from the predictor. However, the Smith predictor is very sensitive to modeling errors, in other words, the model of the controlled system must accurately be known [4]. If there are mismatch between the model of the predictor and the actual system, the closed-loop feedback performance of Smith predictor control may be poor, even unstable [2]. Modified Smith predictor control methods have been presented [5, 6]. Some of them were interested in the study of auto-tuning and adaptive control schemes, others robust control schemes.

Ant colony optimization is a meta-heuristic algorithm inspired by the behavior of real ants, and in particular how they forage for food. ACO can be applied to problems that can be described by a graph, where the solutions to the optimization problem can be expressed in terms of feasible paths on the graph. Among the feasible paths, ACO can be used to find the one with minimum cost. In ACO, a set of artificial ants was created and they cooperate in finding the solution by exchanging information via pheromone deposited on graph edges. The objective of ACO is to find good solutions for combinational optimization problems. In real world, ants move randomly without using other information initially, and lay some pheromone on the ground. After that, an ant moves originally at random until it encounters a previous trail. This ant will then follow the pheromone trail with high probability, and enhances the trail with its own pheromone. Finally, most ants choose the same path with the greatest amount of pheromone deposit. ACO algorithms have been successfully applied to fuzzy control systems [7, 8].

The structure of the paper is as follows. First, a real-time estimation of the system parameters (i.e. the time-delay and the steady-state gain) is accomplished by using a neural network approach, and the estimated parameters are used on line to modify the parameters of the Smith predictor [9], as shown in Fig. 1. Here, $g_p(s)$ is the transfer function without time-delay and $g_m(s)$ is the transfer function without time-delay and the steady-state gain. Secondly, an adaptive fuzzy control based on ant colony optimization is proposed (AFCA). Thirdly, the paper presents the complete process of design of the adaptive Smith predictor and the fuzzy controller for slow time-varying and uncertainty systems with time-delay. Finally, we analyzed the robustness of the control system with respect to an inaccurate model and disturbance rejection capability of the system.

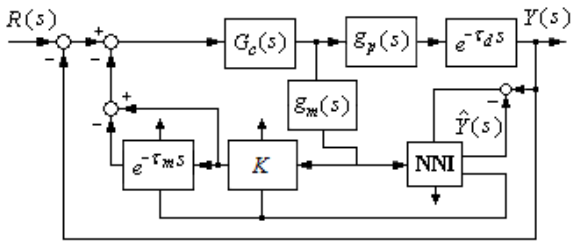



**Fig. 1.** Smith predictor scheme.

## 2. Model Identification

### 2.1. The Neural Network Model for Identification

The time-delay and the steady-state gain of the systems can be estimated by a simple Adaline network [2, 3] with the LMS training algorithm, as shown in Fig. 2.

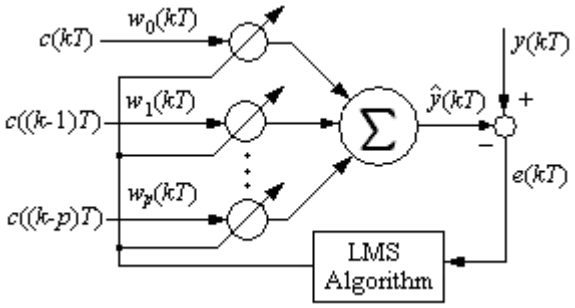



**Fig. 2.** Adaline model for identification.

In this model, $y(kT)$ and $\hat{y}(kT)$ are actual output of the system and output of Adaline network at time *k*, respectively.

The input signal vector of Adaline network at time *k* is shown as

$$\mathbf{C^T}(kT) = [\, c(kT)\,, c((k-1)T)\,, \ldots, c((k-p)T)\,]\,, \quad (1)$$

and the weight vector at time *k* is shown as

$$\mathrm{W}(kT) = [\, w_0(kT), w_1(kT), \ldots, w_p(kT)\,] \quad (2)$$

The output of Adaline network at time k can be expressed as

$$\hat{y}(kT) = \mathbf{C^T}(kT)\mathbf{W}(kT) \quad (3)$$

The error between actual output of the system and output of Adaline network at time k is given as

$$e(kT) = y(kT) - \hat{y}(kT)\,, \quad (4)$$

where the weights of Adaline network are adjusted to minimize the sum of the square error by using the LMS training algorithm. The LMS algorithm can be widely applied when the statistics of the inputs are either unknown or partially known.

The weight vector is updated every T seconds as

$$W[(k+1)T] = W(kT) + \Delta W(kT)\,, \quad (5)$$

where

$$\Delta W(kT) = \begin{cases} \dfrac{\eta e(kT) C(kT)}{C^T(kT) C(kT)}, & C^T(kT) C(kT) \neq 0 \\ 0, & C^T(kT) C(kT) = 0 \end{cases}$$

and $\eta$ is the coefficient that it is used to control the rate of convergence of the algorithm.

A necessary and sufficient condition to obtain the convergence of Eqn.5 is

$$0 < \eta < 1/\lambda_{\max}\,, \quad (6)$$

where $\lambda_{max}$ is the largest eigenvalue of $E[CC^T]$ [2].

### 2.2. Identification of the Time-delay and Gain of the System

Consider a discrete time system described by

$$y(k)=\frac{KB(z^{-1})}{A(z^{-1})}z^{-d}u(k)+\phi(k)$$

and the output without time-delay of the system as

$$c(k)=\frac{\hat{B}(z^{-1})}{\hat{A}(z^{-1})}u(k)+\varphi(k), \quad (7)$$

where $A(z^{-1})$ and $B(z^{-1})$ are the polynomials defined by

$$A(z^{-1})=1+a_1z^{-1}+a_2z^{-2}+\cdots+a_nz^{-n}$$

$$B(z^{-1})=b_1z^{-1}+b_2z^{-2}+\cdots+b_nz^{-m}$$

$K$ and $d$ are the steady-state gain and the time-delay of the system respectively. Further, $u(k)$ is the system input, $\phi(k)$ and $\varphi(k)$ are the stationary white noise with zero mean, unit variance and independence each other.

The output of the neural network for identification is described by

$$\hat{y}(k)=\sum_{i=0}^{p}w_i(k)c(k-i) \quad (8)$$

If the neural network is stable, there is

$$y(k)=\hat{y}(k) \quad (9)$$

or

$$\frac{KB(z^{-1})}{A(z^{-1})}z^{-d}u(k)=\sum_{i=0}^{p}w_i(k)\frac{\hat{B}(z^{-1})}{\hat{A}(z^{-1})}u(k-i) \quad (10)$$

If $\hat{B}=B$ and $\hat{A}=A$, Eqn. 10 can be written by

$$z^{-d}K=\sum_{i=0}^{p}w_iz^{-i} \quad (11)$$

To calculate the derivative of eqn.11 and to set up $z$ =1, the result is written by

$$d=\sum_{i=0}^{p}w_i\cdot i\Big/K \quad (12)$$

If the variable z of Eqn.11 is taken the place of 1, the result is shown by

$$K=\sum_{i=0}^{p}w_i \quad (13)$$

The polynomials $\hat{A}(z^{-1})$ and $\hat{B}(z^{-1})$ of the model can are obtained by employing common identification method.

## 3. Adaptive Fuzzy Control Using ACO

Fuzzy logic provides human reasoning capabilities to capture uncertainties, which cannot be described by precise mathematical models. It has been proven to be very powerful techniques in the area of process modeling and control, especially when the system is difficult to model mathematically, or when the system has large uncertainties and strong non-linearity.

### 3.1. The Design of Fuzzy Controller

A typical structure of a fuzzy control system is shown in Fig. 3. In this structure, the fuzzifier is a mapping from a given input space to fuzzy sets in a certain input universe of discourse. The fuzzy rule base contains a set of fuzzy logic rules. The inference engine matches the rule preconditions in the fuzzy rule base with the input state linguistic terms and performs implication. The fuzzy inference, which simulates a human ability to make decisions using fuzzy logic and approximate reasoning, is an important component of the fuzzy controller. Its reasoning is based on the relations of the fuzzy logic and the rules to carry out. Several types of fuzzy systems have been proposed depending on the types of fuzzy if-then rules and fuzzy reasoning. In this paper, each rule in the fuzzy controller is presented in the following form:

$$R_i: \text{IF } x \text{ is } A_i \text{ and } y \text{ is } B_i \text{ THEN } z=f_i(x,y) \quad (14)$$

where x and y are the input values, z is the output value, and $A_i$ and $B_i$ are the fuzzy sets characterized by their membership functions. IF-parts of the rules describe the fuzzy regions of the input variables and THEN-parts are functions of the inputs.

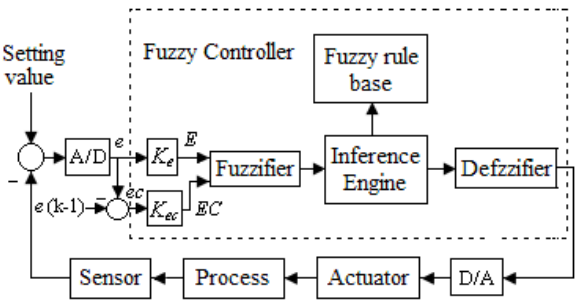



**Fig. 3.** A typical structure of fuzzy control system.

In Fig. 3, $K_e$ and $K_{ec}$ are the quantization parameters, and $K_u$ is the proportion parameter of fuzzy controller. A/D is an analog to digital converter. D/A is a digital to analog converter.

*E* and *EC* are selected to inputs of the controller. They are the system error and the change of error respectively, and corresponding fuzzy variables. Each fuzzy variable is quantified into seven term sets: NB-Negative Big, NM-Negative Medium, NS-Negative Small, ZE-Zero, PS-Positive Small, PM-Positive Medium, and PB-Positive Big. The triangular membership functions for each fuzzy term set and the universes of discourse for each fuzzy variable, including input and output variable, are shown in Fig. 4. The output of the fuzzy controller use equally partitioned fuzzy variable of *E* and *EC*, as shown in Fig. 5.

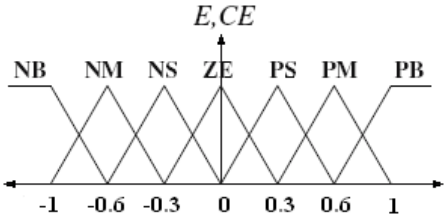



**Fig. 4.** The membership functions.

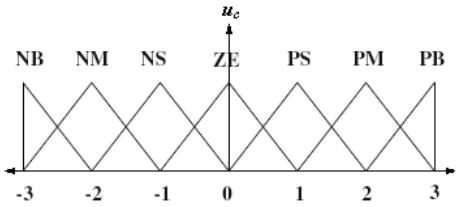



**Fig. 5.** The membership functions.

The fuzzy universe of discourse of the system error *E*, the change of error *EC* and the output signal $u_c$ are defined as

$E = EC = u_c = \{-6,-5,-4,-3,-2,-1,0,+1,+2,+3,+4,+5,+6\}$

The defuzzifier is utilized to yield a non-fuzzy control action from an inferred fuzzy control action by the inference engine. The output of the inference process is a fuzzy set, specifying a possibility distribution of control action. The defuzzification interface converts fuzzy control output to actual control command. There are many methods of defuzzification, a weighted average method in this paper is used by

$$U(k) = \frac{\sum_i \mu_c(u_{ci}) * u_{ci}}{\sum_i \mu_c(u_{ci})}, \qquad (15)$$

where $\mu_{C'}(u_{ci})$ means membership function, and $U(k)$ is the value of control action.

The precise output value is given by the fuzzy controller after the fuzzy output is processed by defuzzification method. The precise control is computed by

$$u(k) = k_u U(k) + \frac{u_H + u_L}{2}, \qquad (16)$$

where $u(k)$ is the actual amount of system control, $k_u$ is the proportional factor of fuzzy controller, $u_H$ is the maximum of control value and $u_L$ is the minimum of control value.

The fuzzy control rules of the controller are expressed in table 1.

**Table 1.** The fuzzy control rules of $u_c$

| EC / E | NB | NM | NS | ZE | PS | PM | PB |
|---|---|---|---|---|---|---|---|
| NB | NB | NB | NB | NB | NM | NS | ZE |
| NM | NB | NB | NB | NM | NS | ZE | PS |
| NS | NB | NM | NS | NS | ZE | PS | PM |
| ZE | NB | NM | NS | ZE | ZE | PS | PM |
| PS | NB | NM | ZE | PS | PS | PM | PB |
| PM | NS | ZE | PS | PM | PB | PB | PB |
| PB | ZE | PS | PM | PB | PB | PB | PB |

### 3.2. The Adaptive Fuzzy Control Using ACO

In this paper, an adaptive fuzzy control system with Smith predictor using ACO is shown in Fig. 6.

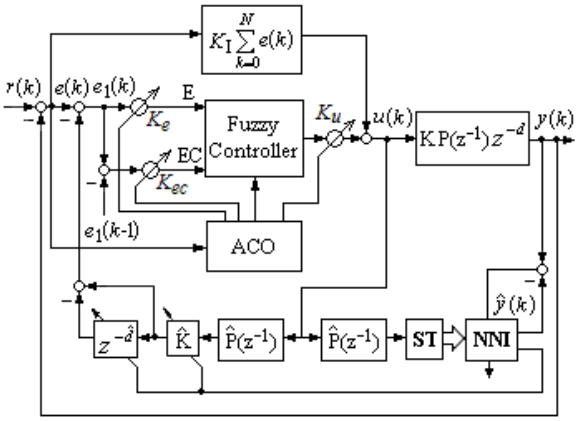



**Fig. 6.** The adaptive fuzzy control system with Smith predictor and the ACO optimization.

In Fig. 6, $e(k)$ is the system error at time $k$ defined as $e(k) = r(k) - y(k)$, where $r(k)$ is the setting value of the system and $y(k)$ is the system output at time k respectively. $K_I$ is the integrator coefficient. The integrator is used to further improve the steady-state quality of the system.

The ACO is employed to search for the optimal parameters $K_e$, $K_{ec}$ and $K_u$ of the fuzzy controller, and the weight factors $\alpha_e$ and $\alpha_{ec}$ of the fuzzy control rules under the objective function aims to minimize the index ITAE. It is considered less large initial errors, emphasizing overshoot and settling time, reflecting the rapidity and accuracy of the control system. ITAE is shown as

$$J(k) = \sum_{k=0}^{N} \left| e(k) \right| kT , \tag{17}$$

where $T$ is the computing step size and $N$ is the total number of computing points.

The fitness function needs to be maximized, using Eqn.18, so it is chosen as

$$f(k) = \frac{1}{1 + CJ(k)}, \tag{18}$$

where $C$ is the weighted coefficient.

The transient and steady state response performance of the control system is directly related to the parameters $K_e$, $K_{ec}$ and $K_u$ of the adaptive fuzzy controller. If the value of $K_u$ is chosen to be large, we may obtain the fast response of the system, but the percent overshoot of the system is increased and the response becomes increasingly oscillatory. When it is decreased to an unsuitable value, response of the system will become slow and may produce steady state error. Therefore the analysis of $K_u$ on-line shows that it ought to be large in initial stage of the response in order to enhance swiftness of the response. When the response of the system is close to steady state value of the system, it ought to be progressively decreased to a steady value, which guarantees a good performance of the system. It is obvious that its value ought to vary with the system response and needs to be automatically adjusted on-line for optimum performance. In order to avoid too large oscillation of the system, the $K_e$, $K_{ec}$ and $K_u$ of the controller are divided into two parts, i.e. $K_e=K_{e0}+\Delta K_e$, $K_{ec}=K_{ec0}+\Delta K_{ec}$ and $K_u=K_{u0}+\Delta K_u$, where $K_{e0}$, $K_{ec0}$ and $K_{u0}$ are the constant obtained by both experience and experiment, and $\Delta K_e$, $\Delta K_{ec}$ and $\Delta K_u$ need to be adjusted by using ACO algorithm.

The weight functions of the error and the change of error are designed as

$$\alpha_e = |E| / (|E| + |EC|) \tag{19}$$

$$\alpha_{ec} = |EC| / (|E| + |EC|) \tag{20}$$

where $\alpha_e + \alpha_{ec} = 1$ must be satisfied and the fuzzy control rules are obtained as

$$U = U_0 + \Delta U \tag{21}$$

where $U_0$ is the constant that is given according to conventional design of fuzzy control rules, and $\Delta$U is designed as

$$\Delta U = < \alpha_e E + \alpha_{ec} EC > \tag{22}$$

$\theta$ of The fuzzy controller need to optimize the parameter set is defined by

$$\Theta = [\ \Delta K_u\ \ \Delta K_e\ \Delta K_{ec}\ \alpha_e\ \ \alpha_{ec}\ ] \tag{23}$$

The parameter optimization of fuzzy controller using ACO can be summed up as a typical continuous space optimization problem. First, the scope of the optimal solution can be estimated based on the nature of the problem, and we obtain ranges of the demand variable. The grids are made in the variable region, the grid node in space corresponds to a state space and ants move between grid nodes. According to the objective function value of each grid node, arts leave a different amount of information on the grids, which will influence the direction of movement of the next batch of ants. The information amount of the grid nodes, which have the small difference of the objective function between the neighboring nodes, is relatively large after a period of time cycles. The space grid nodes of large information amount are found according to the amount of information, and the scope of variables is reduced, ant colony will move near this node. Repeat the above process until they meet the algorithm stop condition.

The m ants are randomly scattered on a spatial grid nodes, while they are optimizing the parameters of fuzzy controller. The evaluation function value of each ant $l$ is defined to difference between the objective function $J_i$ of $i$ node and the objective function $J_j$ of adjacent to j node, it is shown as

$$\Delta J_{ij} = J_i - J_j \tag{24}$$

To select the next path, the state transition probability is defined as follows

$$P_{ij} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\Delta J_{ij}]^{\beta}}{\sum_{r \in \text{allowed}_i} [\tau_{ir}]^{\alpha}[\Delta J_{ir}]^{\beta}}, & \text{if } j \in \text{allowed}_i \\ 0, & \text{otherwise} \end{cases} \tag{25}$$

where $\tau_{ij}$ is the pheromone trail, $\Delta J_{ij}$ is the heuristic information between facility $i$ and location $j$, $\alpha$ and $\beta$

are the parameters that determine the relative influence of the pheromone strength and the heuristic information, and $\text{allowed}_i$ is the feasible neighbourhood of node *i*, that is, only those locations that are still free.

While ants are optimizing the parameters of fuzzy controller, they are randomly scattered on a spatial grid points and the algorithm implement the optimal strategy, which save wizard ant has the best evaluation function value. Then, each ant of ant colony is transferred according to compute the state transition probabilities of eqn. 25. Nearby search mechanism embedded in the search process, i.e. when $\Delta J_{ij} > 0$, ant *l* is transferred from neighborhood *i* to neighborhood j according to the state transition probabilities $P_{ij}$, and when $\Delta J_{ij} < 0$, ant *l* executes its own neighborhood search for obtaining the best parameters.

When the end of a cycle, the number of pheromone on ants moved path is accordingly adjusted in accordance with the following formula.

$$\begin{cases} \tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \\ \Delta\tau_{ij}(t) = \sum_{i=1}^{m} \Delta\tau_{ij}^{l} \end{cases}, \quad (26)$$

where

$$\Delta\tau_{ij}^{l} = \begin{cases} \dfrac{Q}{J_l}, & \text{If ant}_l \in \text{path}_{ij} \\ 0, & \text{otherwise} \end{cases}, \quad (27)$$

where $\text{ant}_l \in \text{path}_{ij}$ denote that ant *l* passed the path (*i*, *j*) in this cycle. $J_l$ is the computed value of the objective function in this cycle and $Q$ is the amount of pheromone that is deposited by an ant. Here $0 \leq \rho < 1$ is the pheromone trail evaporation rate and an adaptive control strategy is employed in order to improve the efficiency of the algorithm for solving in this paper. The evaporation rate of adaptive adjustment is shown as

$$\rho(t+1) = \begin{cases} 0.9\rho(t), & \text{if } 0.9\rho(t) > \rho_{\min} \\ \rho_{\min,} & \text{otherwise} \end{cases} \quad (28)$$

which $\rho_{\min}$ is the minimum value of $\rho$ and it can prevent $\rho$ too small from reducing convergence rate of the algorithm.

In order to increase the search speed, two ants are used to simultaneously search optimal parameters from two extreme points in this optimization strategy. It can effectively improve the global convergence speed of the algorithm.

The implementation of the ACO is presented as follows

1) Setting initiate parameters, pheromone initiate rule, parameters of ACO algorithm and parameter set of fuzzy controller.

2) Ant's solution construction: By moving from node to node in the grid node of the graph model, an ant incrementally constructs a solution in a probabilistic way. An ant moves through adjacent nodes by a decision policy named the state transition probabilities $P_{ij}$ given in eqn. 25.

3) Local pheromone update: After the completion of full solutions at the end of the ants' solution construction step, the pheromone trails are changed. Ants can build an autocatalytic feedback process by adjusting the intensities of pheromone trails. The pheromone evaporation rate of adaptive adjustment is applied to the pheromone trails by eqn. 28 and the local pheromone update progress is performed as in eqn. 26 and Eqn. 27.

4) Local search: Nearby search mechanism is used. The difference value between the objective function $J_i$ of *i* point and the objective function $J_j$ of adjacent to j point is computed by Eqn. 24.

5). Global pheromone update: The elitist strategy is a mechanism to ensure that the information carried by the best solutions can be emphasized. In the global pheromone update step, elitist ant generates an elitist solution set is preserved.

6) Repeate (2) to (5) until the algorithm convergence or the maximum iteration number .

## 4. Experimental Results

Consider the first-order system with time delay

$$\frac{Y(s)}{U(s)} = \frac{K}{Ts+1} e^{-\tau_d s}$$

where $K = 6$, $T = 20$ and $\tau_d = 28$.

The parameters of the ACO algorithm have been chosen as m=30, $\alpha$=1.5, $\beta$=4.3, $\rho_{\min}$=0.2, $\tau_{ij}$=1, $\Delta\tau_{ij}$ (0)=0, $Q$=300 and the total number of cycles $N_c$=100. The $\Delta K_u$ is assumed to be between -2 to 2 and $K_I$ =0.1. The delay $\tau_d$ and the steady-state gain $K$ of the system are estimated by the above introduced identification method. When the number of the network input p is equal to 50 and the sample number q is equal to 50, the estimated parameters that are shown in Fig. 7 (a) and (b).

The Smith control without both the adaptive modified predictor and auto-tuning (SC) is employed in order to compare with the proposed method (AFCAS) in the paper. The output curves of the system of the two control methods for a unit step input are shown in Fig. 8 (a).

When the steady-state gain $K$ and time constant $T$ of the system are reduced to a half, and time-delay $\tau_d$ is increased by one times, i.e. $K$=3, $T$=10 and $\tau_d$ =56, the output curves of the system of the two control methods for a unit step input are shown in Fig. 8 (b).

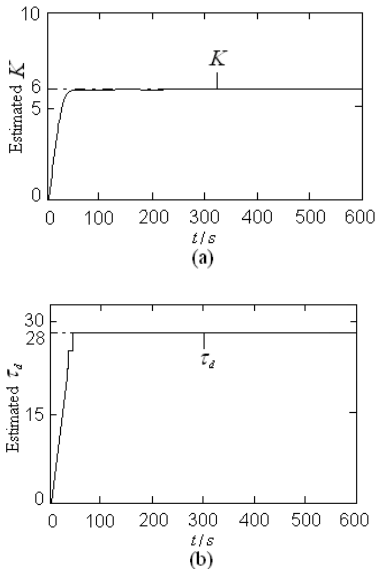



**Fig. 7.** The estimated value of the system parameters.

When the steady-state gain $K$ and time constant $T$ are increased by one times, and delay $\tau_d$ is increased by two times, i.e. $K$=12, $T$=40 and $\tau_d$ =84, the output curves of the system of the three control methods for a unit step input are shown in Fig. 8 (c). Thus it can be seen that the output of Smith control without both the adaptive modified predictor and fuzzy tuning is large oscillatory and the overshoot is very larger. This shows that the traditional Simth control is dependent on accurate mathematical model and is invalid for the control of uncertain systems. The output curves of the proposed control method have a remarkably good performance in the parameters variety. Thus, the proposed control method has good robustness and immunity.

Consider a disturbance of 20 percent of the input when system is running in 400 second, and the output curve of the proposed control method is shown in Fig. 8 (d).

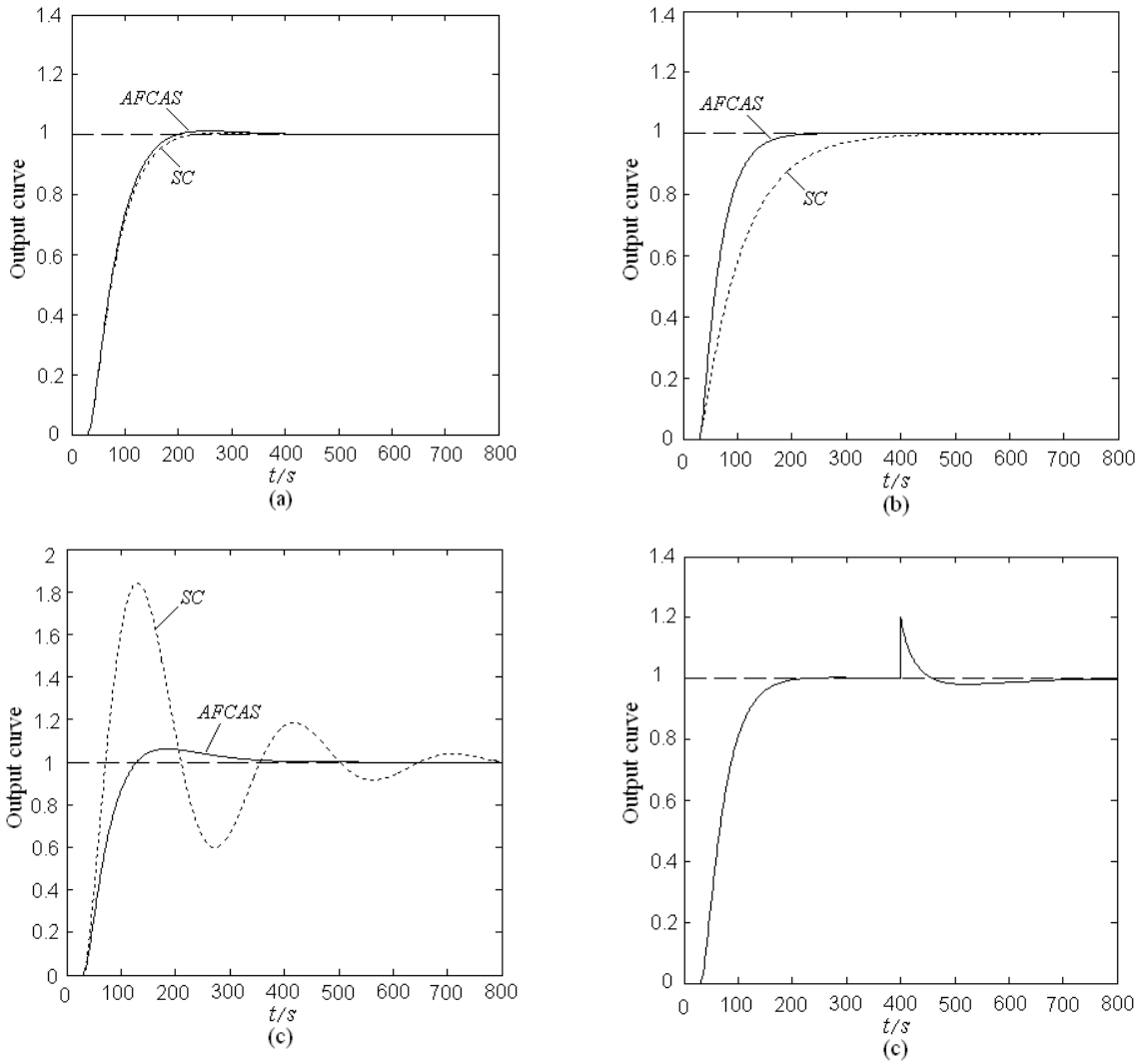



**Fig. 8.** Output curves.

## 5. Conclusions

The unknown systems with time-delay are frequently encountered in industry. Many such systems are often accompanied by parameters slow varying with time and uncertainty. It is very difficult to control such delay systems. We research a new adaptive method using adaptive Smith predictor and adaptive fuzzy control using improved ACO algorithm in this paper. The neural network is used to on-line identify the steady-state gain and the time-delay of the unknown systems with time-delay, and obtained values modify the parameters of Smith predictor in real-time. This enhances the ability of the Smith control method for inaccurate models. Besides, an adaptive fuzzy controller using the ACO algorithm is designed and the ACO algorithm is used to search optimal parameters and weights of fuzzy rules of the fuzzy controller. In order to further improve the steady-state quality of the system, the integrator is used to constitute a dual controller of fuzzy controller plus integrator. We have analyzed the robustness of proposed control method with respect to an inaccurate model and anti-disturbance capacity of the system. Simulation results show that it is an efficient method for slow time-varying and uncertainty systems with time-delay.

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## References

[1] O. J. M. Smith, Closer control of loops with deadtime, *Chem. Eng. Prog*., 53, 5, 1957, pp.217-225.

[2] A. Balestrino, F. B. Verona, and A. Landi, On-line process estimation by ANNs and Smith controller design, *IEE Proc.-Control Theory Appl*., 145, 2, 1998, pp. 231-235.

[3] P. L. Feintuch, N. J. Bershad, and F. A. Reed, Time delay estimation using the LMS adaptive filter-dynamic behavior, *IEEE Transactions on Acoustics, Speech, and Signal Processing*, Assp-29, 3, 1981, pp.571-576.

[4] S. W. Michiel, and S. I. Niculescu, On the delay sensitivity of Smith Predictors, *International Journal of Systems Science*, 34, 8-9, 2003, pp.543-551.

[5] J. Q. Huang, and F. L. Lewis, Neural-network predictive control for nonlinear dynamic systems with time-delay, *IEEE Transactions on Neural Networks*, 14, 2, 2003, pp.377-389.

[6] T. Liu, Y. Z. Cai, and D. Y. Gu, New modified Smith predictor scheme for integrating and unstable processes with time delay, *IEE Proc.-Control Theory Appl*., 152, 2, 2005, pp. 238-246.

[7] C. F. Juang and C. Lo, Fuzzy systems design by clustering-aided ant colony, *International Journal of General Systems*, 36, 6, 2007, pp.623-641.

[8] Cassillas, O. Cordon and, I. F. Viana, Learning cooperative linguistic rules using the best–worst ant system algorithm, *International Journal of Intelligent Systems*, 20, 2005, pp. 433–452.

[9] H. X. Li and B. Z. Luo, Adaptive Control Based on Genetic Algorithm and Fuzzy Tuning for Unknown Systems with Time-Delay, in *Proceedings of the 7th World Congress on Intelligent Control and Automation*, Chongqing, China, 25 – 27 June 2008, pp.8650-8655.

[10] Lai C L, Hsu P L. Design the remote control system with the time-delay estimator and the adaptive smith predictor. *IEEE Trans on Industrial Informatics*, 6, 1, 2010, pp.73-80.

[10] Wang J. D., Zheng W. X., Chen T. W., Identification of linear dynamic systems operating in a networked environment, *Automatica*, 45, 12, 2009, pp.2763-2772.

[11] P. Manju and V. Subbiah, Effect of Changing Membership Functions in the Operation of Fuzzy Based Unified Power Flow Controller in a Power System Network, *Journal of Computational Intelligence and Electronic Systems*, 2, 1, 2013 , pp. 60-65 (6).

[12] Ullah Irfan, Ullah Furqan, Ullah Qurban, and Shin Seoyong, Object Following Fuzzy Controller for a Mobile Robot, *Journal of Computational Intelligence and Electronic Systems*, 1, 1, 2012 , pp. 86-90 (5).

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