Designe of An Adaptive Neuro-Fuzzy Position Controller For A Pneumatic System

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Abstract-**Pneumatic actuators are recently used in many application for robotics and automation such as drilling, sawing, spraying, and gripping. This utilization is due to high speed, low cost, and safety characteristics of these actuators. However, the use of pneumatic systems in position control applications is somewhat restricted due to significant system nonlinearities, caused by air compressibility, friction effects and variations of process parameters with time. In recent years, many researchers tried to solve these restrictions by applying adaptive control mechanism. In this work we used a hybrid structure of fuzzy control and neural networks for the control of a pneumatic actuator. Here the neural network used to adjust all of the output membership functions in the fuzzy logic controller and works as a neural adaption mechanism. The steepest descent learning procedure is implemented and the output from a conventional feedback controller is used as an error by neural network for tuning the parameters of the fuzzy controller. Then, we compared our approach with the fuzzy adaption mechanism. The results obtained by simulation, show better performance of the proposed Adaptive Neuro-Fuzzy Control structure.**

Keywords- **Adaptive Neuro-Fuzzy Controller, Adaption Mechanism, Pneumatic Actuator System,   Position Control**

I. INTRODUCTION

Servo pneumatic systems play important roles in industrial applications because of their main advantages of high speed action capabilities, low cost, cleanliness ease of maintenance, simplicity of operation of these systems relative to other similar hydraulic and electro-mechanical technologies, safe lightweight and good power to weight ratio. However, because the dynamics of these systems are highly nonlinear and their models inevitable contain parametric uncertainties and unmodeled dynamics, researchers have to used adaptive techniques[1], [2], [3]. The two well-known of adaptive techniques, recently used were fuzzy logic, and neural network [4], [5], [6], [7]. For instance, Xiang et al. [8], proposed an Adaptive Fuzzy-PD controller of a position controlled pneumatic system. They applied the meta fuzzy inference system to adjust index of two output membership functions in T-S fuzzy PD like controller to control the plant. In many works researchers mixed fuzzy logic and neural

network because this hybrid structure have the complementary characteristics. The former one has characteristics of linguistic information and logic control, and the later one posses characteristics of learning, fault-tolerance and parallelism. Thus, the development of integrated fuzzy neural networks (FNNs), which possess the merits of both fuzzy logic and neural networks, has grown rapidly [9], [10]. Moreover, the adaptive control schemes that incorporate the techniques of FNNs are widely suggested to use in nonlinear systems [11], [12]. Huang et al.[13],proposed an adaptive neural network controller and a local model network for model prediction in a pneumatic servo system. Local model networks are an online self-learning networks which are able to approach a nonlinear dynamic from input-output data. The controller that they used is a single neuron structure. Atushi et al [14] used online learning method for training Neural Network. They incorporated a model reference, in which the difference between the plant output and model output caused a signal error used for training the NN .Ganesh [15] presented a well-trained Neural Network provides the PI controller with suitable gains depending on feedback representing changes in position error and changes in external load force. These gains should keep the positional response within minimum overshoot, minimum rise time and minimum steady state error. In this structure the NN should be trained offline by input output data that collected from the actual pneumatic system. David C.Cross [16] also used offline trained feed forward multilayer neural network as a controller in their proposed structure.

In this paper we presented a hybrid fuzzy control using neural networks for the control of a pneumatic actuator. The neural network used to adjust all of the output membership functions in the fuzzy logic controller and works as a neural adaption mechanism. The steepest descent learning procedure is implemented and the output from a conventional feedback controller is used as an error by neural network for tuning the parameters of the fuzzy controller. Comparison with the traditional fuzzy adaption technique also is discussed. The results obtained by simulation, show better performance of the proposed Adaptive Neuro-Fuzzy Control (ANFC) structure.

II.   DESIGNE OF ANFC FOR PNEUMATIC SYSTEM

The basic structure of the adaptive control strategy proposedis shown as in Fig. 1 This structure consists of two blocks:Neuro-Fuzzy Controller and learning mechanism.
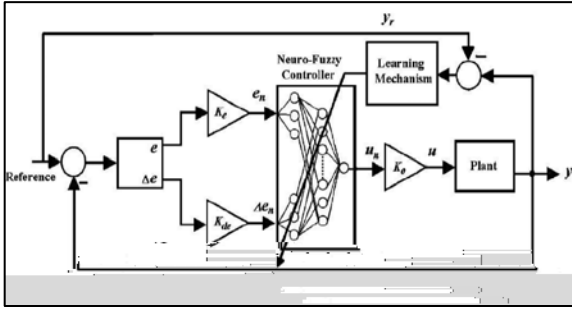

Fig. 1. The basic structure of the adaptive control strategy

As shown in Fig. 2 the NFC with fuzzy singleton rules is configured to have two inputs and one output, which is the control action u_n .
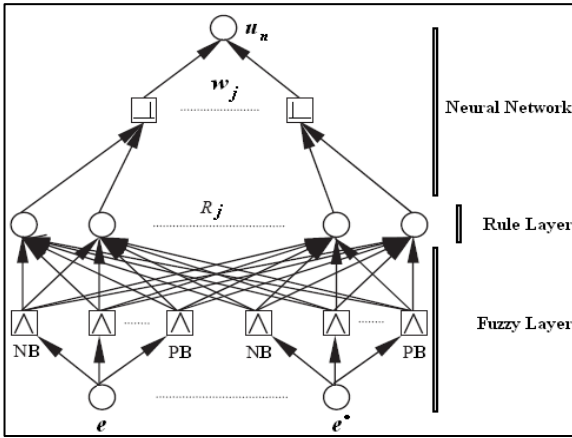

Fig. 2. Neuro-Fuzzy Controller Structure

The NFC inputs are the displacement error $e(kT)$ and the error change rate $\Delta e(kT)$; that formulated in (1) (2):

$$e(kT) = y_r(kT) - y(kT) \tag{1}$$

$$\Delta e(kT) = \frac{(e(kT) - e((k-1)T))}{T} \tag{2}$$

In which, y_r is the set point, y is the actual measured displacement, and T is the sampling time. Three scaling factors k_e, k_{de}, k_o are introduced to produce normalized input and output signals of the fuzzy controller as following:

$$e_n = k_e e \tag{3}$$

$$\Delta e_n = k_{de} \Delta e \tag{4}$$

$$u = k_o u_n \tag{5}$$

Two input linguistic variables e ; Δe and one output linguistic variable u are defined as the inputs and output of the fuzzy controller. The descriptive labels that used for these variables are selected as follows:

$e_j \in$ (NB;NM;NS;Z; PS;PM;PB);

$\Delta e_j \in$ (NB;NM;NS;Z; PS;PM;PB);

$u_j \in$ (NB;NM;NS;NVS;Z;PVS; PS;PM; PB).

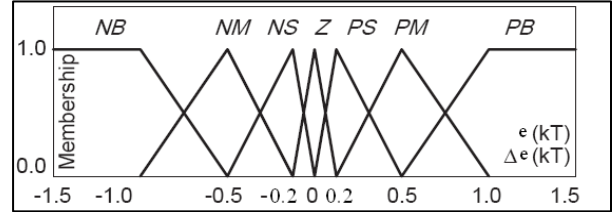The triangular fuzzy sets are chosen for input variables that shown in Fig. 3.

Fig. 3. Input membership function for e , Δe

The linguistic labels used to describe the fuzzy sets are 'negative big' (NB); 'negative medium' (NM); 'negative small' (NS); 'negative very small' (NVS); zero (Z); 'positive very small' (PVS); 'positive small' (PS); 'positive medium' (PM); 'positive big' (PB).

The defined rules of the fuzzy controller are shown in Table I in a matrix format and should be interpreted as follows:

TABLE I

Error change rate							
Error	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	NVS
NM	NM	NM	NM	NM	NS	NVS	Z
NS	NS	NS	NVS	NVS	NVS	Z	PVS
Z	NS	NVS	Z	Z	Z	PVS	PS
PS	NVS	Z	PVS	PVS	PVS	PS	PS
PM	Z	PS	PVS	PM	PM	PM	PM
PB	PVS	PS	PM	PB	PB	PB	PB

RULE TABLE

B IF e IS e_j AND Δe IS Δe_j THEN u_n IS u_j

Generally for simplification of calculation, MIN-PRODUCT method is selected for fuzzy inference, and weight center method is selected for defuzzification.The control output, u_n , is calculated by (6):

$$u_n = \frac{\sum_{j=1}^{M} \mu_j w_j}{\sum_{j=1}^{M} \mu_j} \tag{6}$$

where μ_j is the firing strength of rule j and w_j is a real number of weight in the neural part.

III. ADAPTION MECHANISM

In this section due to comparison purpose, the proposed Nuro-Fuzzy adaption mechanism and the fuzzy adaption method that used in Adaptive Fuzzy-PD Controller [8] will be illustrated.

A. Neuro-Fuzzy Adaption Mechanism

In this paper, the initial input space is heuristically and only roughly configured, while the consequent of the proposed ANFC is determined by the adaptation algorithm. The T-S model of fuzzy control is used in the proposed structure because tuning the consequent of its fuzzy rule does not affect the control action of other rules.

In the proposed adaptation strategy, based on the observed error the particular control actions (weights of NFC) are continuously updated, which are proportional to the firing strength of the fuzzy rules. The learning rule by the steepest descent technique is described as follows:

$$w_i^j(t+1) = w_i^j(t) - \eta_w \frac{\partial E}{\partial w_i^j} \tag{7}$$

where

$$\frac{\partial E}{\partial w_j} = \frac{\mu_j(x)}{\Sigma_{j=1}^M \mu_j(x)}(y - y_r) \tag{8}$$

and i is the fuzzy rule index.

B. Fuzzy Adaption Mechanism

As shown in Fig. 4 in the structure of AFPDC all the linguistic values for output membership functions are similar to a standard fuzzy controller's except for two linguistic values *NVS* and *PVS*: The fuzzy adaption mechanism adjusts an adaptive controller parameter Ma in order to achieve the accurate position control.
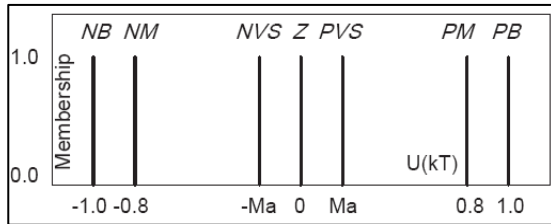

Fig. 4. Output membership function for u_n

In this controller the input membership functions and the control rules are the same as our proposed structure that are shown in Fig. 3 and Table I respectively.
For the fuzzy adaption system, the linguistic labels that used to describe the fuzzy set Ma are: 'small'(*MaS*);'medium' (*MaM*);'big' (*MaB*) . The position of these fuzzy sets on its universe of discourse is shown in Fig. 5.
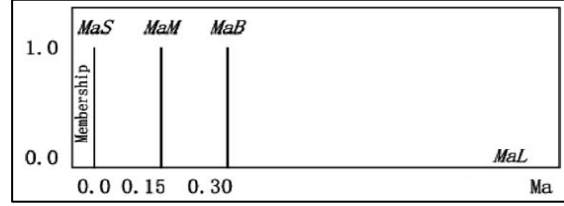

Fig. 5. Output membership function for *Ma*

The controller parameter Ma changes with the normalized error and error change to incorporated adaption ability in AFPDC structure.

For the fuzzy adaption system the meta level rules are defined that is shown in a matrix format in Table II.

TABLE II

Error	Error change rate						
	NB	NM	NS	Z	PS	PM	PB
NB	MaB	MaB	MaB	MaB	MaB	MaB	MaB
NM	MaB	MaB	MaB	MaB	MaB	MaB	MaB
NS	MaB	MaM	MaM	MaM	MaM	MaM	MaB
Z	MaS	MaS	MaS	MaS	MaS	MaS	MaS
PS	MaB	MaM	MaM	MaM	MaM	MaM	MaB
PM	MaB	MaB	MaB	MaB	MaB	MaB	MaB
PB	MaB	MaB	MaB	MaB	MaB	MaB	MaB

META LEVEL RULE TABLE

IV. MODEL OF THE SYSTEM

Dynamics in the pneumatic actuator system was produced by changing in the spring constant in the model that simulates variation in load force. Dynamic model relating between the valve voltage input and the position output is mentioned in [17] and can be determined by following formulas:

$$M\ddot{x} + C\dot{x} + k x = A(P_p - P_n) \tag{9}$$

$$\dot{m}_p = \frac{V_p}{\gamma R T_s}\frac{dP_p}{dt} + \frac{P_p}{R T_s}\frac{dV_p}{dt} \tag{10}$$

$$\dot{m}_n = \frac{V_n}{\gamma R T_s}\frac{dP_n}{dt} + \frac{P_n}{R T_s}\frac{dV_n}{dt} \tag{11}$$

in these equations: M is the piston mass, C is the air damping constant, k is the spring constant, P_p is the pressure in chamber p, A is the bore area, P_n is the pressure in chamber n, V_p is the air volume in chamber p, V_n is the air volume in chamber n, γ is the ratio of specific heat, R is the universal gas constant, T_s the operating temperature, $\dot{m}_p$ is the mass flow rate into chamber p, and $\dot{m}_n$ is the mass flow rate into chamber n.

Due to linearizing the system, a small deviation from proposed equations is considered. The Initial values of the state variables assumed as follows:

$x = 0$, $P_p = P_{p0}$, $P_n = P_{n0}$, $V_p = V_{p0}$, $V_n = V_{n0}$.

consequently, (9)–(11) can be rewritten as:

$$M\Delta \ddot{x} + C\Delta \dot{x} + k\Delta x = A(\Delta P_p - \Delta P_n) \qquad (12)$$

$$\Delta \dot{m}_p = \frac{V_{p0}}{\gamma R T_s}\Delta \dot{P}_p + \frac{P_{p0}}{R T_s}\Delta \dot{V}_p \qquad (13)$$

$$\Delta \dot{m}_n = \frac{V_{n0}}{\gamma R T_s}\Delta \dot{P}_n + \frac{P_{n0}}{R T_s}\Delta \dot{V}_n \qquad (14)$$

where Δ denotes the small deviation value. The proportional flow control valve is used in simulations. Suppose that mass flow rate is identical in both chambers and displacement of the spool valve is proportional to the valve voltage. Then relation between the input voltage deviation and the flow rate deviation can be written as:

$$\Delta \dot{m}_p = K\Delta v \text{ and } \Delta \dot{m}_n = -K\Delta v \qquad (15)$$

where K is proportional valve constant. By simple volume equation,

$$\Delta \dot{V}_p = A\Delta \dot{x} \text{ and } \Delta \dot{V}_n = -A\Delta \dot{x} \qquad (16)$$

Substitute (15) and (16) into (13) and (14) and rewriting them , the following Equations are obtained.

$$\Delta \dot{P}_p = -\frac{\gamma A P_{p0}}{V_{p0}}\Delta \dot{x} + K\frac{\gamma R T_s}{V_{p0}}\Delta v \qquad (17)$$

$$\Delta \dot{P}_n = \frac{\gamma A P_{n0}}{V_{n0}}\Delta \dot{x} - K\frac{\gamma R T_s}{V_{n0}}\Delta v \qquad (18)$$

Rewrite (12), the motion equation then become

$$\Delta \ddot{x} = \frac{A}{M}(\Delta P_p - \Delta P_n) - \frac{C}{M}\Delta \dot{x} - \frac{k}{M}\Delta x \qquad (19)$$

then (17)–(19) are represented in a state-space form. Suppose that state variables is

$$X = \begin{bmatrix} \Delta P_p & \Delta P_n & \Delta x & \Delta \dot{x} \end{bmatrix}^T \quad \text{and} \quad \dot{X} = AX + Bu .$$

$$y = CX + Du \qquad (20)$$

$$\dot{X} = \begin{bmatrix} 0 & 0 & 0 & -\dfrac{\gamma A P_{p0}}{V_{p0}} \\ 0 & 0 & 0 & \dfrac{\gamma A P_{n0}}{V_n 0} \\ 0 & 0 & 0 & 1 \\ \dfrac{A}{M} & -\dfrac{A}{M} & \dfrac{k}{-M} & \dfrac{-C}{M} \end{bmatrix} X + \begin{bmatrix} K\dfrac{\gamma R T_s}{V_{p0}} \\ -K\dfrac{\gamma R T_s}{V_{n0}} \\ 0 \\ 0 \end{bmatrix} \Delta v \qquad (21)$$

$$y = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix} X + \begin{bmatrix} 0 \end{bmatrix}\Delta v$$

In this case, the system transfer function can be determined as

$$G(s) = \frac{\Delta x(s)}{\Delta v(s)} = C(sI - A)^{-1}B = \frac{k1}{s(s^2 + \dfrac{C}{M}s + K_2)} \qquad (22)$$

where

$$k_1 = \frac{\gamma A R T_s K}{M}\left(\frac{1}{V_{p0}} + \frac{1}{V_{n0}}\right), \quad k_2 = \frac{k}{M} + \frac{\gamma A^2}{M}\left(\frac{P_{p0}}{V_{p0}} + \frac{P_{n0}}{V_{n0}}\right)$$

V. SIMULATION AND RESULTS

To assess the control performances of the proposed position controlled pneumatic system, comparison between ANFC and AFPDC were performed by computer simulations in MATLAB environment. In the simulation all initial weights in the neural part of ANFC are set to zeros. This occurred in the controller which has no knowledge about the plant. Also in AFPDC, *NVS* and *PVS* index of output membership functions are set to zero. Simulation results of ANFC and AFPDC response are shown in Fig. 6.

To evaluate the adaption mechanism in changing of the plant parameters, the spring constant is changed at time 196s. The output response in dynamic situation is shown in Fig. 7. From Fig. 7 can observed that, the ANFC has better performance rather than AFPDC in dynamic situation.

When load force changed at time 196s, the output response of the ANFC reached set point faster than AFPDC and also after changing time the ANFC can track the reference signal better than the AFPDC with no overshooting in response .
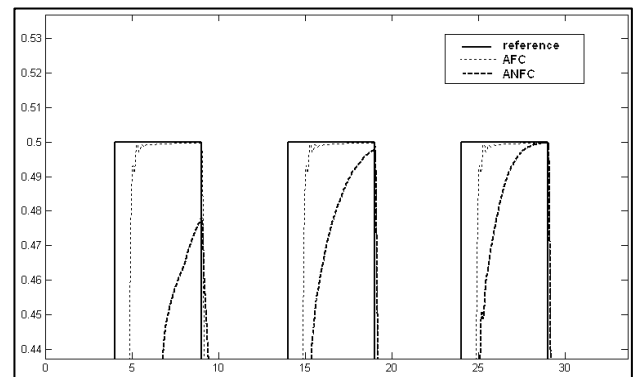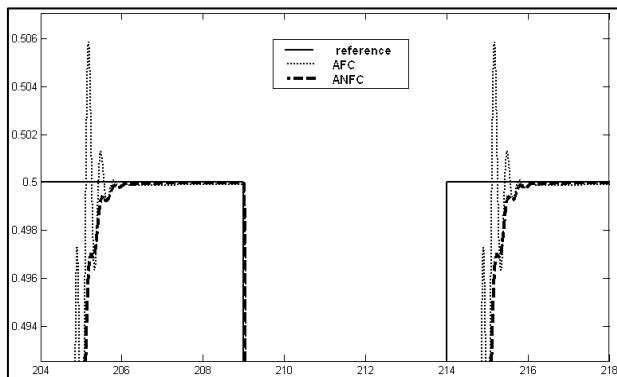

(a)
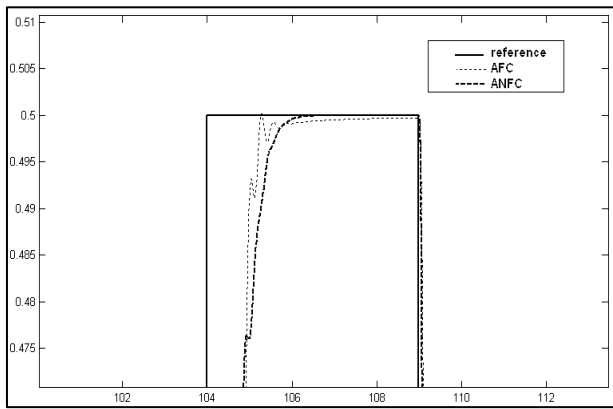
(b)

Fig. 6. Output response comparison in static situation:
(a)Transient response of ANFC and AFPDC during learning (b)Transient response of ANFC and AFPDC after learning
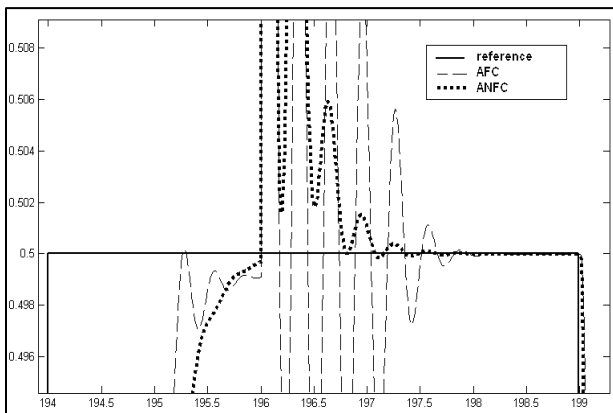
(a)

(b)

Fig. 7. Output response comparison in parameter changing of pneumatic system: (a)Controllers response at changing time , (b)Controllers response after changing time.

VI.   CONCLUSION

In this paper, an Adaptive Neuro-Fuzzy Controller (ANFC) for the Pneumatic actuator system based on the steepest descent learning algorithm has been presented. The simulations carried out with a third order plant by subsequently changed parameters, satisfactorily verified the validity and the better performance of the proposed adaptive algorithm rather than Adaptive Fuzzy-PD Controller (AFPDC).

The proposed adaptive algorithm can find the appropriate weights of neural network part that represent the positions of the fuzzy output sets on its universe of discourse. This is evident from the   obtained simulation results, where the transient responses of the system output have shown an improvement when the learning period was passed.

The use of an ANFC to control pneumatic actuator systems is recommended due the satisfactory results obtained in this investigation.

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