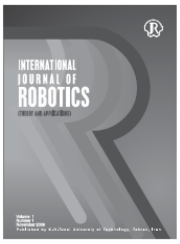

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Position Control of Pulse Width Modulated Pneumatic Systems: an Experimental Comparison

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ABSTRACT

In this study, a new adaptive controller is proposed for position control of pneumatic systems. Difficulties associated with the mathematical model of the system; in addition to the instability caused by Pulse Width Modulation (PWM) in the learning-based controllers using gradient descent, motivate the development of a new approach for PWM pneumatics. In this study, two modified Feedback Error Learning (FEL) methods are suggested and the their effectiveness are validated by experimental tracking data. The first one is a combination of PD (Proportional–Derivative) and RBF (Radial Basis Function) and in the second one; RBF is replaced by ANFIS (Adaptive Neuro-Fuzzy Inference System). The robustness to varying mass is also examined. The experimental results show that the proposed algorithms, especially with ANFIS, are able to give good performance regardless of any uncertainties.

Abbreviations

PWM	Pulse Width Modulation	MLP	Multi-Layer Perceptron
FEL	Feedback Error Learning	BP	Back Propagation
PD	Proportional-Derivative	GS	Gain Scheduling
CFC	Conventional Feedback Controller	DOF	Degree Of Freedom
ANFIS	Adaptive Neuro-Fuzzy Inference System	FL	Fuzzy Logic
NN	Neural Network	RBF	Radial Basis Function
INFC	INtelligent Feedforward Controller	SSE	Sum Square Error
NB	Negative Big	NS	Negative Small
ZE	ZEro	PB	Positive Big
PS	Positive Small	MF	Membership Function

Nomenclature

w_i	The i th weight parameter in RBF/ i th firing strength from layer 2 in ANFIS	M	Number of neurons in RBF
$d_{\min}$	Minimum duty cycle of valves	u	Controller output
u_i	Controller output corresponding to the inflection in PWM/ i th ANFIS input	d_i	Duty cycle corresponding to the inflection in PWM
P	Number of inputs in RBF	η	Learning rate

σ_{ij}	Width of the Gaussian MFs associated with the j th fuzzy linguistic term and the i th input variable in layer 1 (ANFIS)/ Width of Gaussian function associated with j th input and i th neuron (RBF)	c_{ij}	Mean of the Gaussian MFs associated with the j th fuzzy linguistic term and the i th input variable in layer 1 (ANFIS)/ Mean of Gaussian function associated with j th input and i th neuron (RBF)
l	Number of rules in ANFIS	r_n	Current set point
μ_{2k}	k th MF of second input in ANFIS	μ_{1j}	j th MF of first input in ANFIS
$x_d(t)$	FEL command signal	O_{ij}^{1}	j th label for i th input in layer 1
O_i^k	i th output from layer k in ANFIS	$\tau_h(t)$	INFC output
$\phi_i(.)$	RBF activation function	$\tau(t)$	FEL output
$E(k)$	Cost function at time k	d_a, d_b	Duty cycle of valve A and B
$e(k)$	Error signal measured at time k	y	RBF output
θ	RBF Tuning parameters	$\tau_{fb}(t)$	CFC output
$\bar{w}_i$	i th normalized firing strength from layer 3 in ANFIS	k_p	PD proportional gain
μ_{ij}	The membership grade associated with i th input and j th fuzzy linguistic term	u_{pd}	PD controller output
$\{p_i, q_i, r_i\}$	ANFIS conclusion parameter set	T_d	PD derivative time
$x(t)$	Plant output	LT	Number of fuzzy linguistic terms

1. Introduction

Due to the advantages of pneumatic systems as low cost, easy maintenance and serviceability, high speed, cleanliness and high force-to-mass ratio [1], pneumatic systems are emerged as good alternatives for electric motors and during the past few years, variety applications have been reported for them [2,3].

Although the application of pneumatics for driving of mechanical systems is well established, the accurate control for such systems is difficult to be achieved due to inherent nonlinearities such as friction, uncertainty, air compressibility, the possible presence of unknown disturbances coming from leakage of valves and external perturbations. In addition, the mathematical model of a pneumatic system which typically characterized by high-order non-autonomous dynamics with number of unknown parameters like friction makes the controller design problem more challenging [4].

To cope with some of these problems, several advanced control algorithms, especially adaptive and robust control algorithms have been proposed, but in most previous works, bulky and expensive servo-valves have been used (e.g. [4-6]). The application of on/off solenoid valves, instead of the servo-valve, for velocity and position control, effectively reduces the cost and weight of equipment and decreases time, however due to their limitation response time and discrete on/off nature, the complexity of the control system is increased and fine motion control is difficult to be achieved. Pulse Width Modulation (PWM) can effectively approximate the flow properties of a servo-valve with on/off solenoid valves. The first attempt which aimed at applying control technique based on PWM scheme dates back to 1987 by Nuritsogo and after that 1997 by Varseveld and Bone, which the second attempt led to a novel PWM that had a linear velocity and a small deadband and later used by researchers, i.e. [7-12].

Difficulties associated with the mathematical model of the pneumatic system especially with PWM algorithm, can be eliminated by using model-free estimators like neural network (NN) and fuzzy logic (FL) which share the common ability to deal with the uncertainties and noise [13]. Approximately, there is no work on use of NN as a direct controller for pneumatic systems and NNs have been applied as a system identifier and friction compensator in control of pneumatic systems [14]. Recently, FL has been used as an independent controller or in combination with the others to control of pneumatic systems, e.g., as a gain scheduling (GS) [16-19]. The combination of fuzzy rules with the learning attribute of NNs for changing the fuzzy parameters in the framework of the adaptive network can make an adaptive controller called Adaptive Neuro-Fuzzy Inference System (ANFIS) [20]. Although good performance could be achieved by using adaptive neuro-fuzzy for force control in pneumatic systems with proportional valve [21], with PWM algorithm,

asymptotic stability can't be achieved by use of the partial derivative of the plant output with respect to the input (system's Jacobean) in error correction process based on the gradient-based learning methods like gradient descent. If direct and indirect learning methods [22] can't satisfy the aims of controller, the system identification can be useful [23, 24]. In addition to, Feedback Error Learning (FEL) strategy can be used to eliminate the system's Jacobean. This technique is a nonlinear adaptive and 2DOF (Degree Of Freedom) controller and consists of intelligent and conventional in feedforward and feedback paths, respectively. In this strategy, the Conventional Feedback Controller (CFC) is responsible for global asymptotic stability of the overall system; and an Intelligent Feedforward Controller (INFC) is adapted to learn the control system, this INFC, which is working parallel to CFC, takes the control task, after CFC provides stabilization and decays through the time. The sufficient and necessary condition to guarantee the hyper stability of FEL is bounded and converged to zero tracking error [25-29]. During the past few years, the effectiveness of this technique for different systems has been proved by several researchers (e.g. [25, 27, 28]).
The focus of this paper is the position control of a pneumatic actuator with FEL and using PWM algorithm, first RBF is used as an INFC instead of usual Multi-Layer Percepron (MLP), which is formal in FEL, and PD is proposed as a CFC and then RBF is replaced by ANFIS in the FEL framework to study its behaviors in this method.
In this paper, after introducing pneumatic systems and PWM algorithms in two next sections and focusing on proposed controller in section 4, in two final sections, results will be presented.

2. Pneumatic system

Schematic diagram of a pneumatic system is shown in Fig.1.

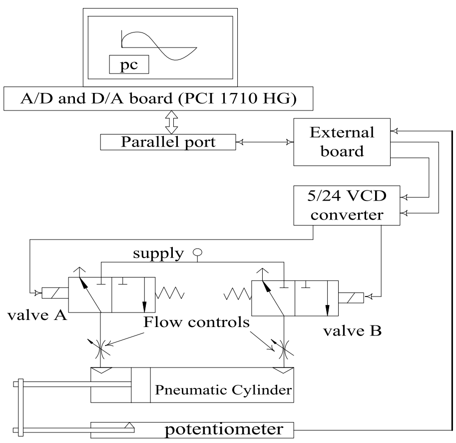


Fig. 1: Schematic diagram of the pneumatic system

As shown in this Fig, the system consists of one double acting pneumatic cylinder with cushioning sections (at both ends), two 3/2 on/off solenoid valves (as command elements), connecting tubes, flow control valves, which is used to change the energy-absorbing capacity, a linear transducer for measuring piston displacement, data acquisition board, extra electrical board to convert input voltage to the proper operating voltage for each valve and a computer to produce the duty cycle of each valve based on the controller output and according to PWM algorithm.

3. Pulse Width Modulation Algorithm

To overcome problems such as dead zone, input/output nonlinearity and low response speed, in using on/off solenoid valves, the transformation of the controller output was selected as shown in Fig. 2. In this algorithm, the duty cycle of each valve shouldn't be lower than d_{min}, where d_{min} is the ratio of valve time response to PWM period and once either valve A and B is set at d_{min}, the duty cycle of the other valve is increased at twice the slope to maintain a linear input/output relationship [7, 9].

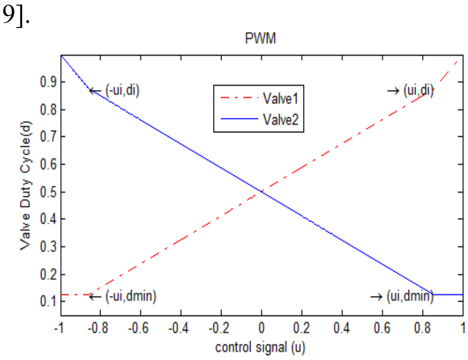


Fig. 2: The scheme of PWM algorithm

4. Controller

As aforementioned, the main idea of FEL is the combination of classical and intelligent controller into a 2DOF controller with inverse model in feedforward path. Fig. 3 illustrates the FEL architecture. As shown in this figure, the input to the plant $(\tau(t))$ consist of the output of the feedforward controller $(\tau_h(t))$ and the output of the CFC $(\tau_{fb}(t))$ [25] and the objective of the control is to minimize the error (e) between the command signal $(x_d(t))$ and the plant output $(x(t))$.

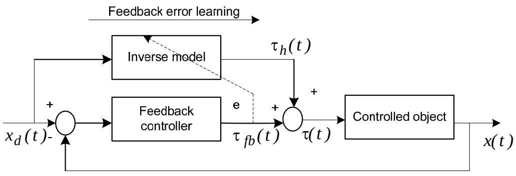


Fig. 3: Feedback error learning scheme [26]

The concepts of RBF and ANFIS are briefly described in the following sections.

4.1. Radial Basis Function Neural Network

Fig.4 shows the RBF network.

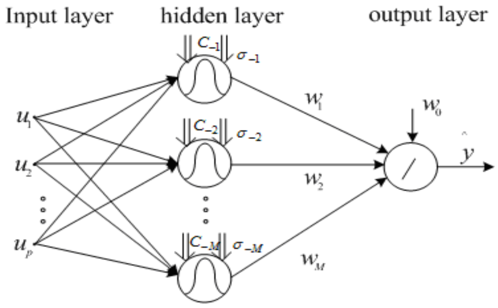


Fig. 4: Radial Basis Function network [30]

As shown in this figure, the input layer is made up of source nodes (sensory units) that connect the network to its environment. The second layer, the only hidden layer in this network, applies a nonlinear transformation from the input space to the hidden space; the output layer is linear, supplying the response of the network to the activation pattern to the input layer. The output of RBF can be summarized in the following equation:

$$y=\sum_{i=0}^{M} w_i\phi_i\left(\sqrt{\sum_{j=1}^{p}\left(\left(u_j-c_{ij}\right)/\sigma_{ij}\right)^2}\right)\quad with\ \phi_0=1.$$

Where $\phi_i(.)$ defines: $\phi_i(x_i)=\exp\left(-x_i^2/2\right)$.

The aim of the training algorithm is to adjust the network weights through minimization of following cost function:

$$E(k)=-1/2\,e^2(k) \tag{2}$$

Where in FEL e defines: $e=\tau-\tau_{fb}=\tau_h$

By using the back propagation (BP) learning algorithm, the weighting vector of RBF $(\theta=[c,\sigma,w]^T)$ is adjusted such that the error defined in (2) becomes less than a desired threshold value. The well-known BP algorithm may be written briefly as:

$$\theta(k+1)=\theta(k)+\eta\left(-\partial E(k)/\partial\theta(k)\right) \qquad ($$

Where the gradient of $E(.)$ in (3) with respect to an arbitrary weighting vector can be computed using recursive applications of chain rule [30].

In this study, a RBF network with two inputs, r_n and r_{n-1} and five neurons is proposed. Also each parameter is learnt by one special learning rate which is chosen to provide the stability of the network in one hand and the satisfactory of speed convergence in other hand; however these two objectives are in contradiction to each other and establishing a compromise between them, with chosen appropriate learning rates, is necessary.

4.2. Adaptive Neuro-Fuzzy Inference System

ANFIS is a fuzzy inference system in the framework of adaptive networks, then this technique possesses advantages of FL and NN. It combines the capacity of fuzzy reasoning in handling uncertain information and the capacity of artificial neural network in the learning of process for achieving optimal control objectives [25]. The ANFIS type III structure is shown in Fig. 5. As shown in this Fig, ANFIS can be described as a five-layered neural network. Layer 1 executes a fuzzification process, layer 2 executes the fuzzy AND on the antecedent part of the fuzzy rules, layer 3 normalizes MFs (Membership Functions), layer 4 executes the conclusion part of the fuzzy rules and finally, the last layer computes the output of the fuzzy system by summing up the outputs of layer four.

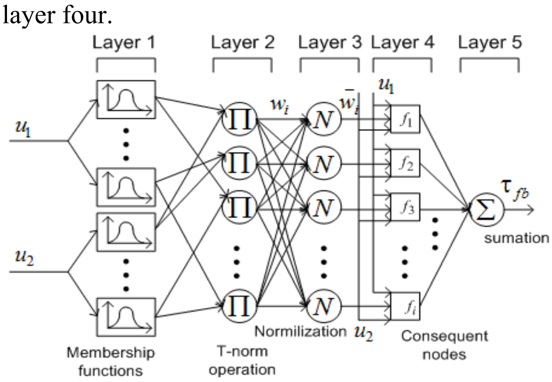


Fig. 5: Structure of the ANFIS (type III ANFIS)

The feedforward equations of the ANFIS with two inputs are as follows:

$$O_{ij}^1=\mu_{ij}(u_i)=\exp\left(\tfrac{1}{2}\left(\left(u_i-c_{ij}\right)/\sigma_{ij}\right)^2\right);\quad i=1,2$$

$$O_i^2=w_i=\mu_{1j}(u_1).\mu_{2k}(u_2);\quad i=1,2,...,l.\quad j,k=1,2,..$$

$$O_i^3=\bar{w}_i=w_i\Big/\sum_l w_l;\quad i=1,2,...,l.$$

$$O_i^4 = \bar{w}_i \, f_i = \bar{w}_i \left(p_i u_1 + q_i u_2 + r_i \right); \quad i = 1, 2, ..., l.$$

$$O_1^5 = \sum_l \bar{w}_l \, f_l = \sum_l w_l f_l \Big/ \sum_l w_l$$

In Fig. 5 adaptable parameters $(\theta = [c, \sigma, p, q, r]^T)$ associated with square nodes (layer 1 and 4) can be affected by the learning process to minimize the cost function, which is presented in equation (2) [15, 20, 25, 31]. In this study, an ANFIS type III with two inputs and one output is proposed (r_n and r_{n-1}), every input is divided into five linguistic terms: NB (negative big), NS (negative small), ZE (zero), PS (positive small) and PB (positive big), and all the possible fuzzy reasoning rules are chosen $(l = 25)$. Like RBF, three learning rates are chosen, two learning rates for parameters of antecedent part and one for conclusion parameters.

4.3. Proportional-Derivative

In this study, PD is used as CFC in FEL framework. PD controller output can be presented like this [32]:

$$u_{pd}(s) = k_p e(1 + T_d s) \tag{9}$$

The combination of feedback and feedforward in FEL framework is shown in Fig. 6 (INFC is RBF or ANFIS controller). In this Figure, input and output are denoted with $r_d(n), r(n)$, and d_a, d_b mean the duty cycle of valve A and B, respectively.

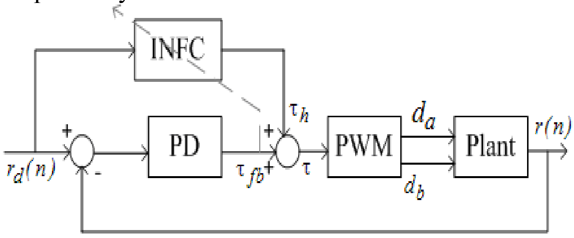


Fig. 6: block diagram of the control system

5. Experimental results

In this section the results of experimental studies are presented. For experimental study, a pneumatic servo system, which is shown in Fig. 7, is set up. The proposed set up have two 3/2 on/off solenoid valves (type: FESTO, MHE2-MS1H-3/2G-M7 with 140 mm cylinder stroke), two flow control valves (type: FESTO-GRO-1/8) and a double acting pneumatic actuator (type: FESTO-DSNU-25-140-PA). The displacement of the cylinder was measured by a linear potentiometer (type: GEFRAN-LT-M-0200-S). An ADVANTECH PCI-1710-HG multifunctional card is installed in an IBM-compatible computer to interface with the experimental hardware and a compressor (supply in Fig. 1) is responsible for papering the compressed air.

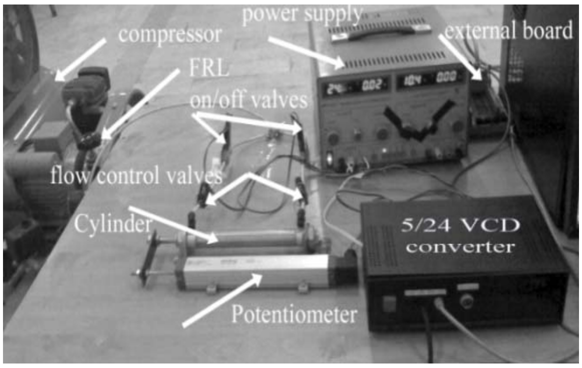
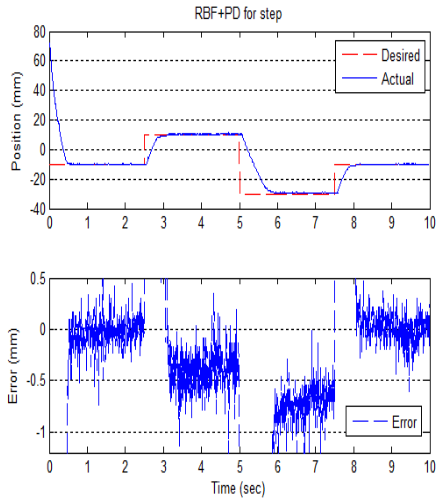


Fig. 7: photograph of the system setting

For showing the effectiveness of the suggested FEL controllers, system response to sinusoidal wave and step are shown. In addition to, simulations studies on the developed system have been carried out by Matlab-Simulink software and to have an appropriate controller output, which can be interpreted by PWM algorithm, all references (set points) converted to mete and then exerted to the system.

In Figs 8 to 9, it is shown that the ANFIS as INFC in FEL framework can cause better performance in comparison with RBF as INFC.



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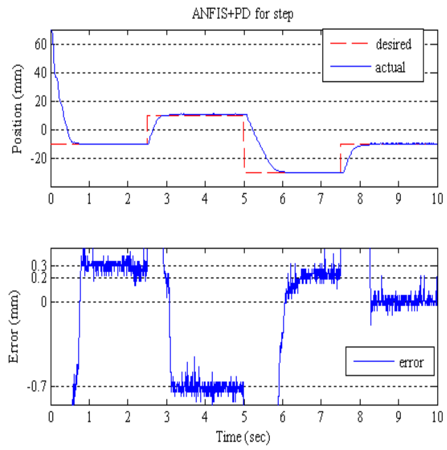
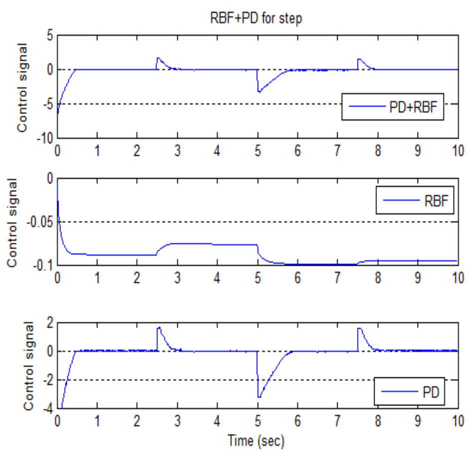


(b)

Fig. 8: Experimental result with step reference and its error (a) RBF and PD, (b) ANFIS and PD in FEL framework



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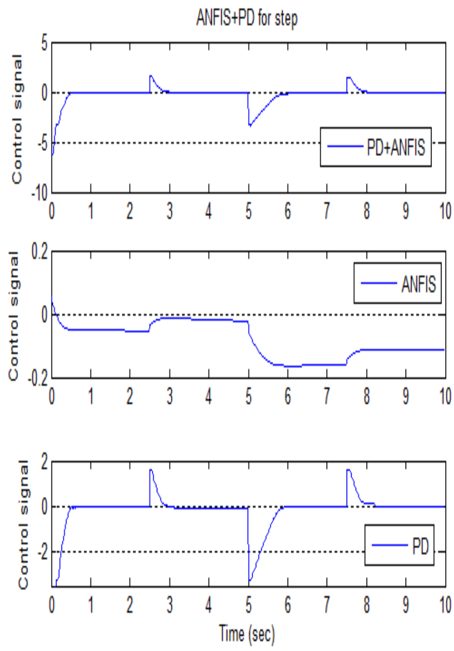
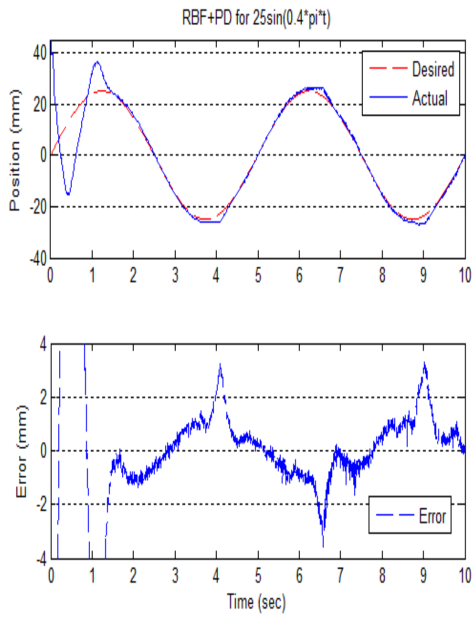


(b)

Fig. 9: Total controller output and the portion of every controller with step reference (a) RBF and PD, (b) ANFIS and PD in FEL framework

The system's response to sinusoidal wave with amplitude (25mm) and frequency (0.2Hz) in Figs 10 to 11 can be interpreted like the step system response.



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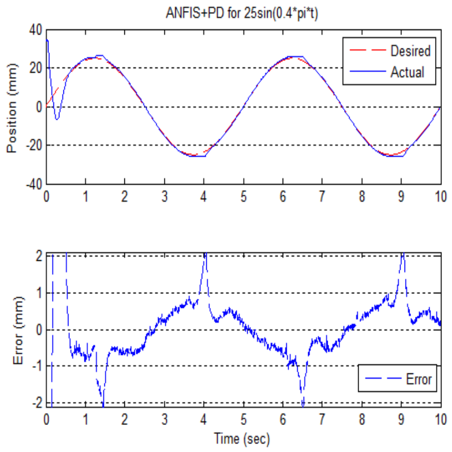
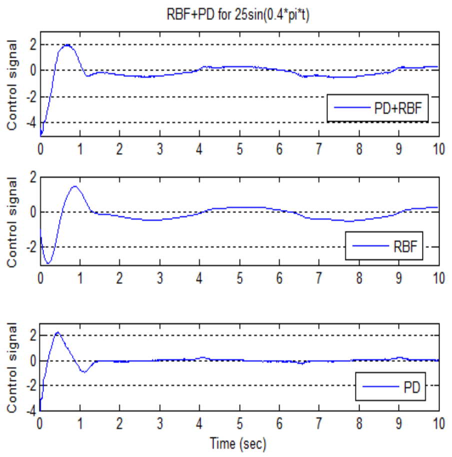


(b)

Fig. 10: Experimental result with $25\sin(0.4\pi t)$ reference and its error (a) RBF and PD, (b) ANFIS and PD in FEL framework



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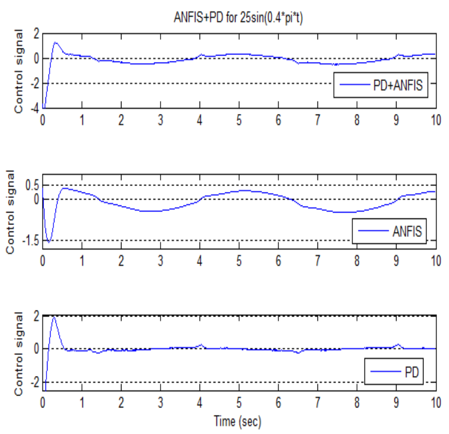


(b)

Fig. 11: Total controller output and the portion of every controller with $25\sin(0.4\pi t)$ reference (a) RBF and PD, (b) ANFIS and PD in FEL framework

Since the system considered here contains uncertainties, we would like to compare the performances associated with the FELs with those from the PD-control. Fig. 12 presents the result of the PD-control under the same experimental conditions.

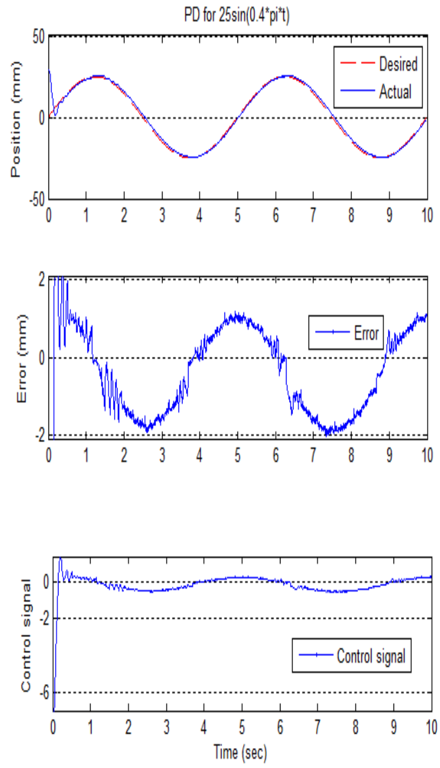
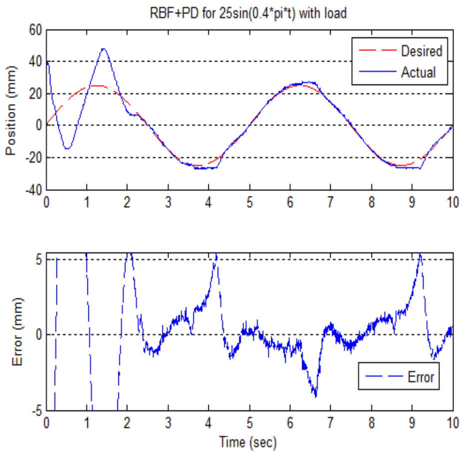


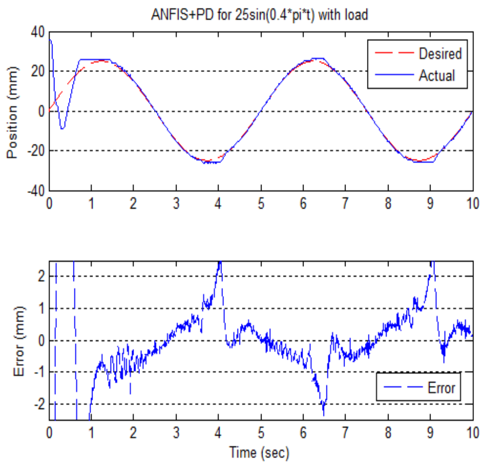
Fig. 12: Experimental result using PD with $25\sin(0.4\pi t)$ reference, its error and control signal

Therefore the effectiveness of the proposed strategies can be confirmed by giving significant improvement in the system performance, regardless of any uncertainties.

The proposed controllers are robust; the robustness to varying mass is also examined. The original mass of piston, rod assembly mass and external load mass (without payload) is around 450gr. The addition of horizontal payload increased this mass by around four times to 1800gr and the system was subjected to the same sinusoidal wave test sequence as before, with the same condition and without retuning. Figs 13 and 14 are focused on system's response to sinusoidal wave in the presence of extra payload.

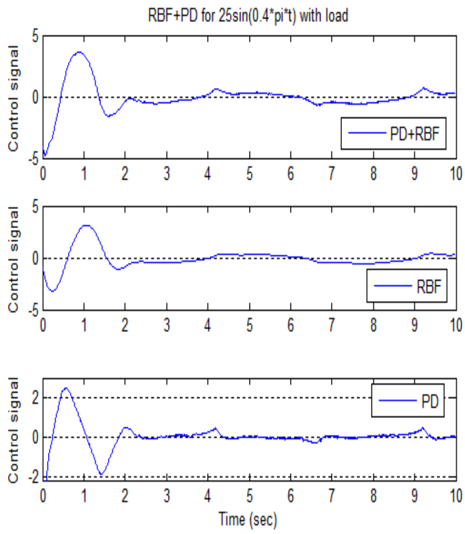


(a)

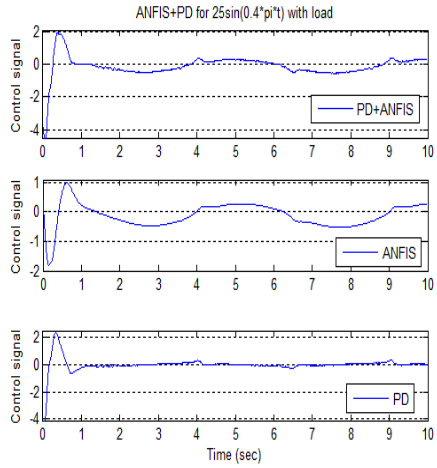


(b)

Fig. 13: Experimental result with $25\sin(0.4\pi t)$ reference and its error after adding load (a) RBF and PD, (b) ANFIS and PD in FEL framework



(a)



(b)

Fig. 14: Total controller output and the portion of every controller with $25\sin(0.4\pi t)$ reference after adding load (a) RBF and PD, (b) ANFIS and PD in FEL framework

As shown and expected, the proposed FEL methods benefit from the robustness with essence of stability and performance, and ANFIS can tolerate new condition better than RBF. Again, to show an ill-posed condition of PD-control, Fig. 15 is devoted to the result of the PD-control under same experimental conditions and in the presence of the payload.

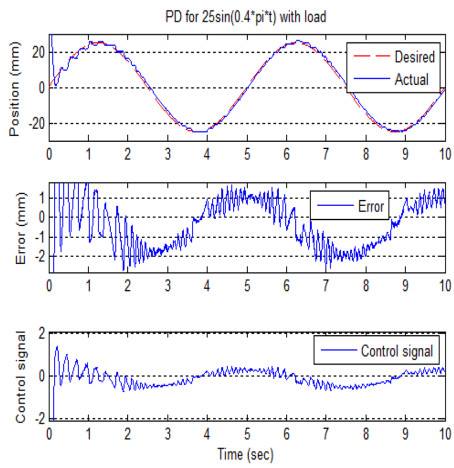


Fig. 15: Experimental result using PD with $25\sin(0.4\pi t)$ reference, its error and control signal after adding load

The ineffectiveness of PD-control in encountering with new operating condition has been expected due to PD features. In Table I related attributes of the proposed controllers in response to sinusoidal wave are summarized. The aspects, which have been listed in this table, confirm the effectiveness of ANFIS over RBF in FEL framework.

6. Conclusion

In this paper, two new adaptive controllers based on modified FEL approaches are proposed for position control of pneumatic actuators with PWM and the effectiveness of each controller is validated on an experimental setting.

Table. 1: attributes of proposed controller in response to $25\sin(0.4\pi t)$

Controller / Attribute	Before adding load		After adding load	
	PD+RBF	PD+ANFIS	PD+RBF	PD+ANFIS
Total SSE (m^2)	3.3907e-2	2.7205e-2	4.5748e-2	3.8761e-2
SSE after settling time (m^2)	0.08217e-2	0.095714e-2	0.17382e-2	0.11305e-2
Total control effort	8.4540e+2	6.3571e+2	14.083e+2	8.9602e+2
Control effort after settling time	1.7268e+2	1.7499e+2	2.0954e+2	1.8498e+2
Settling time (s)	1.725	0.54	1.885	1.1
Maximum overshoot (m)	11.793e-3	———	17.781e-3	5.6659e-3
Maximum undershoot (m)	20.058e-3	15.935e-3	21.710e-3	19.389e-3

In these proposed approaches, modification on FELs strategies were done by adoption of RBF and ANFIS in the feedforward paths, respectively, instead of MLP neural network.
The experimental results and various performance indices illustrate that the proposed FEL with ANFIS as INFC has better control performance in comparison with the RBF as INFC. In addition to the experimental results justify the feasibility of the control strategy.

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