

A Neural Network Based Fuzzy Controller For Pneumatic Circuit

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Abstract

Pneumatic circuits are widely used in industrial automation, such as drilling, sawing, squeezing, gripping, and spraying. Furthermore, they are used in motion control of materials and parts handling, packing machines, machine tools, food-processing industry and in robotics.

In this paper, a Neural Network based Fuzzy PI controller is designed and simulated to increase the position accuracy in a pneumatic servo circuit where the pneumatic circuit consists of a proportional directional control valve connected with a pneumatic rodless cylinder. In this design, a well-trained Neural Network with a simplest structure provides the Fuzzy PI controller with suitable input 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 steady state error and compensate the effect of applying external load force. A comparison between this type of controller with a conventional PID type shows that the PID controller failed to keep the cylinder position with minimum steady state error and failed to compensate the effect of applying external load force as compared with the results when using a Neural Network based Fuzzy PI type controller. This is because of nonlinearities that exist in the pneumatic circuit. Thus, the position response using Neural Network based Fuzzy PI controller is better with an average of improvement in position accuracy of (11 %).

مسيطر مضرب معتمد على شبكه عصبيه يستخدم للدوائر الهوائيه

الخلاصة

تستخدم الدوائر الهوائيه ضمن تطبيقات واسعه ومنها في الصناعه والآتته وكمثال على ذلك تستخدم في عمليات الحفر وقطع الخشب وضغط ومسك المواد والطلاء . وإضافة الى ذلك تستخدم في السيطرة على عمليات نقل المواد وحمل أجزاء المواد وفي مكائن التغليف والصناعات الغذائية والروبوتيات . تم في هذا البحث تصميم وتمثيل مسيطر مضرب متناسب - متكامل معتمد على شبكه عصبيه لغرض زيادة الدقه في الموقع في الدائره المؤازره الهوائيه حيث تتكون الدائره الهوائيه من صمام سيطره متناسب إتجاهي موصل مع إسطوانه هوائيه بدون عصا . وتم كذلك في هذا التصميم تدريب شبكه عصبيه بأصغر هيكله بصوره جيده لتقوم بتزويد المسيطر المضرب متناسب - المتكامل بقيم مناسبه لربح مدخلي المسيطر والتي تعتمد في إختيارها على التغذية العكسيه لتغيير قيم الخطأ في الموقع والتغيير في قوة الحمل الخارجي . حيث يجب أن يؤثر ربحا المدخلين في الحفاظ على تصرف الموقع ضمن أقل قيمه لتجاوز الهدف وأقل قيمه للخطأ في

أستقرار الحاله وكذلك تعويض تأثير تسليط قوة الحمل الخارجي . وقد تمت المقارنه بين نتائج هذا المسيطر مع مسيطر تقليدي من نوع متناسب - متفاضل - متكامل وتبين أن المسيطر التقليدي قد فشل في الحفاظ على موقع الأسطوانه وبأقل قيمه للخطأ في أستقرار الحاله وكذلك فشل في تعويض تأثير تسليط قوة الحمل الخارجي مقارنة مع نتائج مسيطر مضرب متناسب - متكامل معتمد على شبكه عصبيه والسبب في ذلك يعود الى ال- خطيه الموجوده في الدائره الهوائيه مقارنة مع المسيطر موضع البحث الذي نجح في تحقيق المواصفات المطلوبه . لذلك فإن نتائج المسيطر المصمم كانت أفضل وبمعدل نسبة تحسن في دقة الموقع تبلغ 11% .

Introduction

There are three prominent mechanisms used to power motion control: electromechanical, hydraulic and pneumatic. Electromechanical systems use motors to drive motion. Hydraulic systems use incompressible fluids, usually oil or water, to transport energy while pneumatic systems use a compressible fluid, usually air [1].

Electromechanical systems have the advantage of very controlled mechanisms that operate as linear systems. Their disadvantage is that they often are expensive and heavy for high power applications. Hydraulic systems behave less linearly, but are often very efficient for high load applications, such as construction equipment. Their disadvantages are high weight and the viscous force that slow the motion, thus limiting speeds. For high load applications where speed and weight are not important, hydraulic power is ideally suited [1].

Pneumatic actuation systems have

The 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, light weight and good power to weight ratio, but due to the compressible nature associated with the fluid and the quick speed, it is more difficult to control [2, 3].

Pneumatic actuation systems are widely used in industrial automation, such as drilling, sawing, squeezing, gripping, and spraying. Also, they are used in motion control of materials and parts handling, packaging machines, machine tools, food processing industry and in robotics; e.g. two-legged robot [4].

However, the use of pneumatic systems in position and force control applications is somewhat difficult. This is mainly due to the nonlinear effects in pneumatic systems caused by the phenomena associated with air

compressibility, nonlinear effects in pneumatic system components, valve dead-band, significant friction effects in moving parts, restricted flow, time delay caused by the connecting tubes, oscillations of air supply pressure and load variations [1].

Due to the analytical complexity involved it is a very challenging task to obtain an accurate mathematical model of a pneumatic actuator controlled system, which can satisfactorily describe the behavior of the control process. Using mathematical modeling and numerical simulations, a non-linear model can be obtained, which can give good prediction for dynamic behavior of the system and can be used to build a control structure and obtain systems of higher accuracy.

A number of authors have proposed different models and controllers of pneumatic circuits. Design procedure and experimental implementation of a PID controller was also presented by **Situm *et al.*** in 2004[5]. The PID controller was tuned according to optimum damping in order to achieve precise position control of a pneumatic servo drive. The controller was implemented by extending the proposed PID controller with friction compensator with the gain scheduling Fuzzy control. **Sepehri and Karpenko** [6] documented in 2004 the development and experimental evaluation of a practical nonlinear position controller for a typical industrial pneumatic regulator that gives good performance for both regulating and reference tracking tasks.

Quantitative feedback theory was employed to design a simple fixed-gain PI control law that minimizes the effects of the nonlinear control valve flows, uncertainty in the physical system parameters and variations in the plant operating point.

In this paper, a Neural Network based Fuzzy PI controller is designed and simulated to increase the position accuracy in a pneumatic servo circuit which consists of a proportional directional control valve connected with a pneumatic rodless cylinder. In this design, a well-trained Neural Network with simplest structure provides the Fuzzy PI controller with suitable input 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 steady state error and compensate the effect of applying external load force.

Fuzzy logic PI controller:

Fuzzy logic control is similar to the man-kind thinking method. This controller has become one of the most successful of today's technologies for developing sophisticated control system. It is used in all technical fields including control, modeling, image and signal processing and expert systems [7].

A Fuzzy controller is a nonlinear controller because it generates nonlinear mapping from input variables to output variables. There are several reasons to use the Fuzzy

controller for example, it is simple and easy to implement and has a smooth behavior.

However, the proportional plus integral control equation is:

$$V_C(t) = K_p.e(t) + K_i.\int e(t).dt \quad (1)$$

where V_C is the output of the controller, K_p is the proportional gain, K_i is the integral gain and e is the error value:

$$e(t) = X_{ref}(t) - X(t) \quad (2)$$

where $X_{ref}(t)$ is the desired output and $x(t)$ is the actual output. It is clear from equation (1) that there is an integration of the error and it is known that there is a difficulty in formulating rules depending on an integral error because it may have very wide range of universe of discourse. To overcome this problem, the integration is removed by taking the derivative of equation (1) with respect to time. Thus, the equation will be [8]:

$$\frac{d}{dt} V_C(t) = K_p.\frac{d}{dt} e(t) + K_i.e(t) \quad (3)$$

and the equation in discrete form is:

$$\Delta V_C(k) = K_p.\Delta e(k) + K_i.e(k) \quad (4)$$

where $\Delta V_C(k)$ is the derivative of the output of the controller in discrete form and:

$$\Delta e(k) = e(k) - e(k-1) \quad (5)$$

The discrete output of the integral of the controller is:

$$V_C(k) = V_C(k-1) + \Delta V_C(k) \quad (6)$$

The indices (k) and $(k-1)$ represent the present sample and the previous sample instants respectively. It is observed from equation (4) that the

controller needs the error and change of error as inputs where the input gains are K_p and K_i respectively. The output of the equation must be integrating to obtain $(V_C(k))$. However, the MATLAB SIMULINK (Ver. 7.4) model representation of the Fuzzy PI controller as shown in Fig. (1).

Design of Neural Network Based Fuzzy PI Controller:

In order to increase the robustness of the Fuzzy PI controller, a Neural Network based Fuzzy PI controller is used. In this approach, a well-trained Neural Network with a simplest structure provides online the Fuzzy PI controller with appropriate gains (K_p and K_i) according to the change in operating conditions, which is selected to be the error in position (Error) and external load force (F_L).

In order to train this Neural Network, patterns that contain different operating conditions are used as inputs and patterns that contain the optimal values of gains are collected from several simulations for the closed loop Fuzzy PI controlled servo pneumatic circuit are used as outputs. Selection of gains is done according to a certain performance index (PF(t)); i.e. K_p and K_i that makes PF minimum is the optimal Fuzzy PI gains with respect to each input pattern (Error and F_L) [9]. These patterns are used to train the Neural Network and the output of the Neural Network gives optimal values of Proportional gain (K_p) and Integral gain (K_i).

In this work, the performance index is selected to minimize the overshoot

and steady state error of the cylinder position response according to the following equation:

$$PF(t) = \text{Overshoot} * K_1 + \text{Steady state error} * K_2 \quad (7)$$

where K_1 and K_2 are weighting factors chosen to be 20 and 80 respectively. Details of the selection algorithm and the procedure of implementation are explained in below [9]:

Step 1) Divide K_p ($K_{p_min} < K_p < K_{p_max}$) and ($K_{i_min} < K_i < K_{i_max}$) into several equal intervals respectively.

Step 2) For each K_p :

a) gradually increase the value of K_i one interval per time while ($PF(t+1) < PF(t)$).

b) if $PF(t+1) > PF(t)$ is detected, decrease the value of K_i by half the interval gradually until $PF(t+1) < PF(t)$.

c) Increase K_i by 1/4 the interval gradually until $PF(t+1) > PF(t)$ is detected again.

d) Optimal K_i with respect to the selected K_p is $K_{i_optimal} = (K_i(t) + K_i(t+1))/2$.

Optimal $PF(t)$ with respect to the selected (K_p , $K_{i_optimal}$) pair is $PF_{optimal} = (PF(t+1) + PF(t))/2$.

Step 3) Among all (K_p , $K_{i_optimal}$) pairs obtained in Step 2, find the optimal pair that possess the minimum $PF_{optimal}$.

Simulation of a Neural Network Based Fuzzy PI controller of Servo pneumatic circuit:

The design of a Neural Network based Fuzzy PI controller is done by connecting a Fuzzy PI controller model with the SIMULINK model of servo pneumatic circuit where the details of this model are explained in [10]. The circuit consists of a cylinder as a linear drive of a part model number DGPL from Festo company [11]. It is a double acting rodless cylinder with internal piston diameter of 18 mm and stroke length of 300 mm.

This cylinder is used in several applications for controlling the speed and position such as, elevators and in door controlling. Moreover, the valve used in this circuit is selected to be a proportional directional control valve of model number MPYE-5 1/8LF-010-B. It is a control application valve, where the valves switching techniques control the acceleration and velocity. It is a 5/3 way valve and it is normally closed with an electrical type whilst the type of rest is a mechanical spring with permissible supply pressure as maximum to 10 bar. The input set-point voltage is varied from 0 to 10VDC in central position of 5V [12]. However, the specifications of the circuit are list in [13].

The Fuzzy PI controller has two inputs; error and change of error (e and Δe), (Equation 4), and one output

(V_c). The membership function of each input and output will selected to be

triangular type with a normalized domain [-1, 1] as shown in Fig.(2) and Fig. (3) respectively. Each universe of discourse is selected to be seven fuzzy sets ranging from the negative side to the positive side as N_B , N_M , N_S , Z , P_S , P_M and P_B , which represent the linguistic variables of the fuzzy sets. The letters N, Z, P, B, M and S represent Negative, Zero, Positive, Big, Medium and Small respectively.

According to the number of memberships in each input, the Fuzzy PI controller will have $7*7=49$ rules. The selection of those rules based upon the knowledge of the behavior of the error and change of error. After several trials, the rules are selected to be as shown in Table (1). Initial gains of the controller are selected to be $K_p=0.1$, $K_i=1$ and $K_o=10$. However, the Fuzzy PI controlled pneumatic system model is shown in Fig. (4).

A Neural Network with Tan-Sigmoid activation functions are used in the hidden layers whereas linear activation functions are used in the output layer is designed. The error in position and external load force are divided into intervals where error in position is chosen within the range of (-0.3 - 0.3) in step of 0.001 and the external load force is chosen within the range of (1-64) N in step of 1 N. Furthermore, K_P is limited within the range of (0.01-1) and K_I is limited within the range of (1-20). Using a

SIMULINK model shown in Fig. (5) to collect patterns of training, several

simulations were done and a total of 10217×4 input-output patterns were collected. By using *Levenberg-Marquardt* optimization algorithm with a learning rate of 0.001 in the aim to get a minimum size and structure of Neural Network with high accuracy, a Neural Network is trained after 1000 epochs with 1 hidden layer of 25 nodes and mean square error of ($MSE=0.000298742$). The SIMULINK Neural Network block diagram is generated eventually. Finally, this SIMULINK block of Neural Network is connected with a Fuzzy PI controller that is used to control the pneumatic system. The block diagram of the complete Neural Network based PI controlled system is shown in Fig. (5).

As the reference position input with no external load force to the closed loop system is applied, the controller tries to maintain the position of the cylinder while following the reference position with minimum overshoot (0)m and minimum steady state error within (min/max) range of (0-0.0065)m. The responses of the position of cylinder, the reference position input and the error in position are shown in Fig. (6-a). The Neural Network reads the error in position and the values of external load force and recalls the optimal values of Fuzzy controller gains (K_P and K_I) to keep the position response of the cylinder within the required performance as can be shown in Fig. (6-b).

In order to test the controller under the effect of variable load force, a reference position input and an

external variable load force are applied to the pneumatic system model, responses of the position of cylinder, the reference position input and the error in position are shown in Fig.(7-a). It can be noticed that the controller tries to keep the position of the cylinder with minimum overshoot (zero)m and minimum steady state position error within (min/max) range of (0-0.0326)m in spite of the effect of changing load force. Moreover, responses of changing the parameters of the controller and the shape of external load force are shown in Fig. (7-b).

Design of PID controller for Pneumatic circuit:

The PID controller is widely used across industry. It is easy to implement and relatively easy to tune because of the controller simplicity which puts limitations on its capabilities in dealing with complex control problems, such as the Hysteresis problem.

The PID controller equation in time domain is [8]:

$$V_c(t) = KP.e(t) + KI.\int_0^t e(t)dt + KD.\frac{de(t)}{dt} \quad (8)$$

where KP is the proportional gain, KI is the integral gain and KD is the Derivative gain.

The PID controller is connected with to the pneumatic circuit model and the SIMULINK model of the PID controlled Pneumatic system is shown in Fig. (8).

By tuning the controller to achieve cylinder position with minimum overshoot, minimum steady state error

with the compensation of applying external load forces, it was found after several trials that the best gains of the controller to be KP=81, KI=67 and KD=98. Now, by applying a variable reference displacement input and variable external load force, the error has decreased slightly and output displacement rises slowly. The PID controller does not track the model's reference input displacement. The overshoot is (zero)m but with a steady state error within (min/max) range of (0.005-0.029)m. Thus, PID controller fails to keep the cylinder position according to the required position accuracy. This is, of course, because of nonlinearities that exist in the pneumatic model as shown in Fig. (9).

Conclusions

In this paper, a Neural Network based Fuzzy PI controller was designed and simulated to increase the position accuracy and minimize the overshoot in pneumatic servo circuit. In this design, a well-trained Neural Network provides the Fuzzy PI controller with the suitable gains according to each feedback that contains the change in error in position and the change in external load force. These gains should keep the response of cylinder position within minimum overshoot and minimum steady state error and compensate the effect of applying external load force. These characteristics are satisfied without and with the effect of applying external variable load force.

A comparison between the results of the designed controller with conventional PID controller shows that the PID type fails to keep the cylinder position within the minimum steady state error and could not compensate the effect of applying external load force as the Neural Network based Fuzzy PI controller did, an average of improvement in position accuracy of (11 %). This is, of course, happening because of nonlinearities that exist in the pneumatic model and leads to the conclusion that using the proposed Neural Network based Fuzzy PI controller has the potential to compensate for the nonlinearities. In the Neural Network Based Fuzzy PI controller, the dynamic behavior of the closed loop system are changing, by changing the proportional and integral gains of the controller and thus by changing the position of closed loop poles and zeros at the same time. Moreover, results conclude that the Neural Network based Fuzzy PI controller has a simple structure according to the number of hidden layers and the number of neurons per layer and can be implemented by hardware.

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Table (1) Rule base of Fuzzy PI controller.

De e	N _B	N _M	N _S	Z	P _S	P _M	P _B
N _B	Z	N _B	N _B				
N _M	N _B	N _S	N _B	Z	N _B	P _M	N _B
N _S	N _B	N _B	N _B	N _B	P _M	P _B	P _B
Z	P _B	P _B	P _M	P _S	P _B	N _M	N _B
P _S	P _M	P _M	P _M	P _B	P _B	Z	P _B
P _M	P _B	P _M	P _B	P _B	P _B	P _M	N _B
P _B	N _B	P _B	P _M	P _M	P _B	P _M	Z

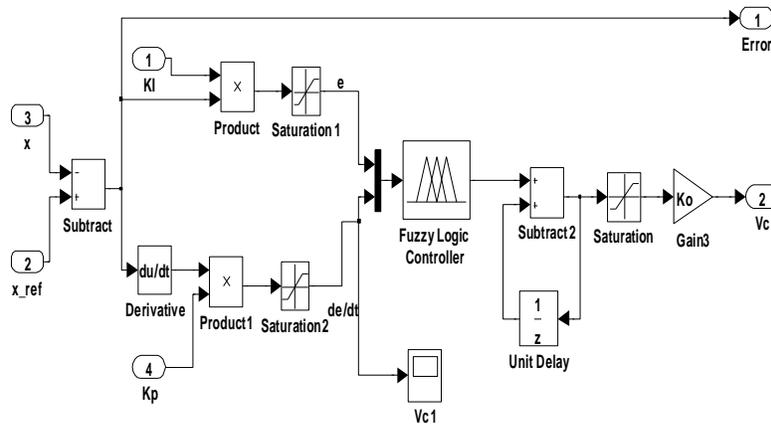


Figure (1) Simulink of Fuzzy PI controller.

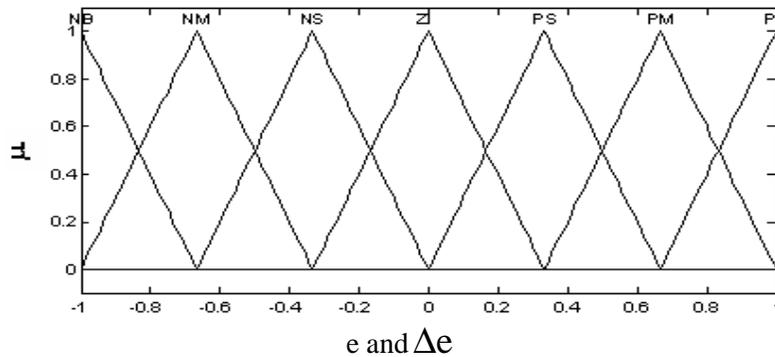


Figure (2) Membership functions of the inputs (e and Δe).

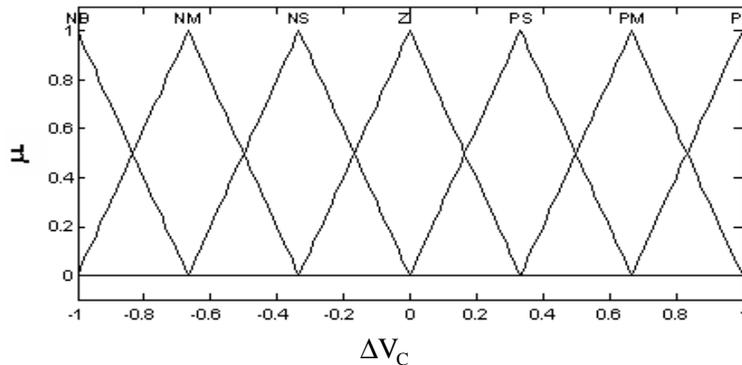


Figure (3) Membership function of the controller output.

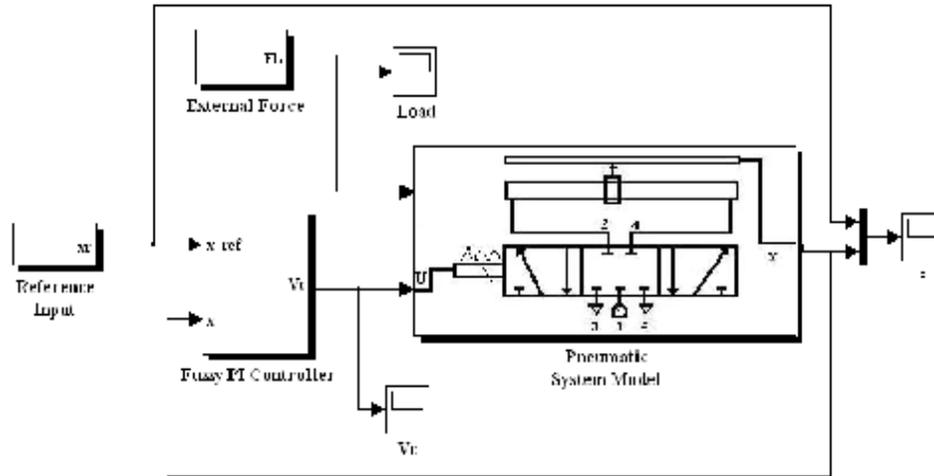


Figure (4) SIMULINK of Fuzzy PI controlled Pneumatic system.

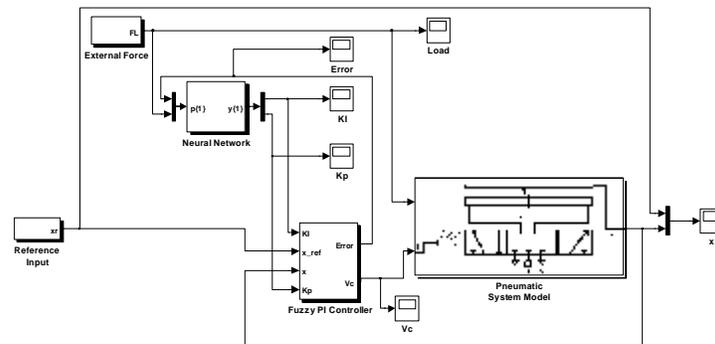


Figure (5) SIMULINK of Neural Network Based Fuzzy PI controlled Pneumatic circuit.

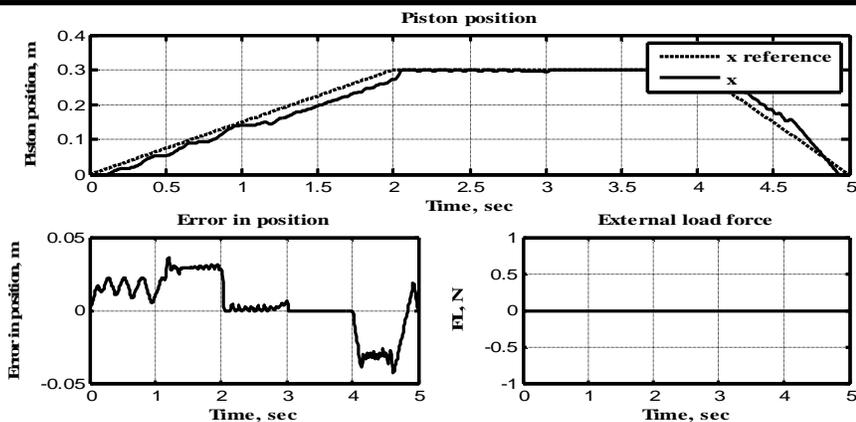


Figure (6-a) Closed loop no-load responses of piston position, error in position of Neural Network based Fuzzy PI controlled Pneumatic circuit.

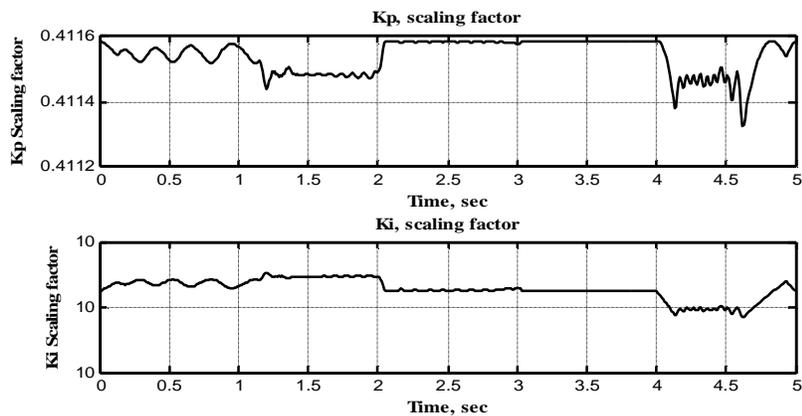


Figure (6-b) Variations of Fuzzy PI controller gains generated by the Neural Network.

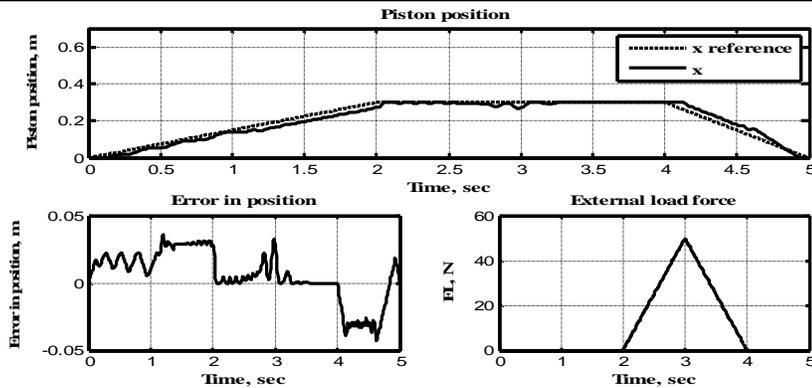


Figure (7-a) Closed loop variable-load responses of piston position, error in position and external load of Neural Network based Fuzzy PI controlled Pneumatic circuit.

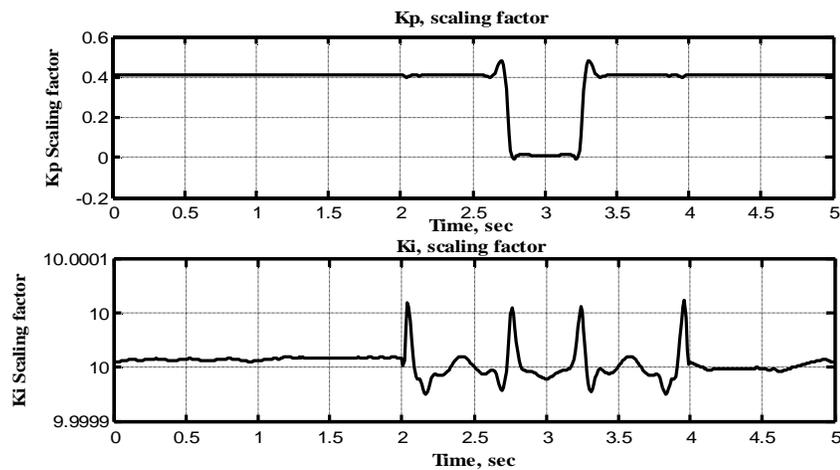


Figure (7-b) Variations of Fuzzy PI controller gains generated by the Neural Network.

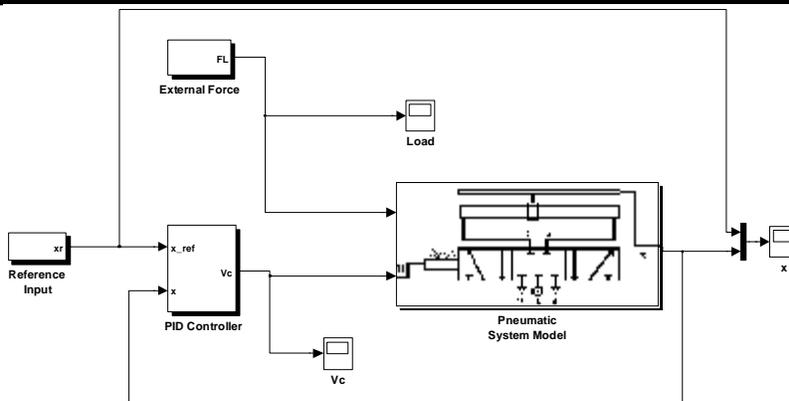


Figure (8) SIMULINK of PID controlled Pneumatic circuit.

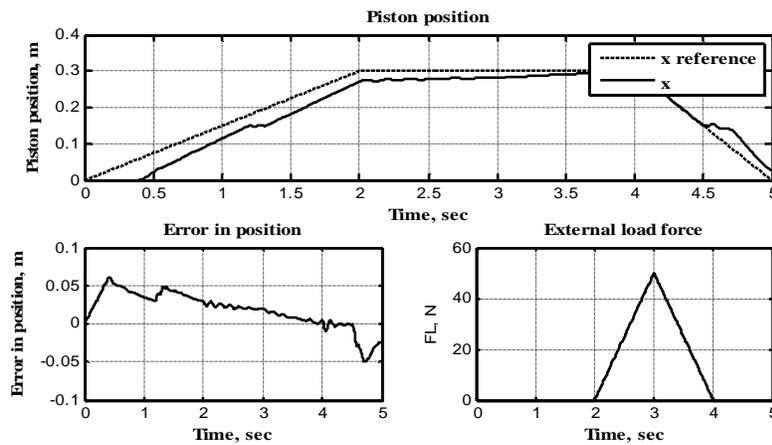


Figure (9) Closed loop variable-load responses of piston position, error in position and external load of PID controlled pneumatic circuit.