Design of a Neural Network Based Intelligent PI Controller for a Pneumatic System

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Abstract **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, packing machines, machine tools, food processing industry and in robotics; e.g. two-legged robot. In this paper, a Neural Network based intelligent PI controller is designed and simulated to increase the position accuracy in a pneumatic servo actuator where the pneumatic actuator consists of a proportional directional control valve connected with a pneumatic rodless cylinder. In this design, 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. A comparison between this type of controller with a conventional PI type shows that the position of cylinder using a conventional PI controller keeps jittering even when the cylinder reaches the required steady state. This is because of nonlinearities that exist in the pneumatic actuator. This jitter does not persist when a Neural Network based Intelligent PI type controller is used.**

Index Terms **Pneumatic System, Neural Network, PI controller.**

I. 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 whereas pneumatic systems use a compressible fluid, usually air. Electromechanical systems have the advantage of highly controllable 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.

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Their disadvantages are high weight and 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 as mentioned in [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 lightweight and good power to weight ratio, but due to the compressible nature associated with the fluid and the high speed, it is more difficult to control as mentioned in [2] and referred to in [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 as mentioned in [4] and referred to in [5].

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 as mentioned in [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 behaviour of the control process. Using mathematical modelling and numerical simulations, a non-linear model can be obtained, which can give good prediction for dynamic behaviour 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 systems. Thomas [6] explored advanced control strategies for proportionally controlled pneumatic actuators. A significant constraint apparent in this study is that the strategies developed can only work within the architecture of an industrial programmable logic controller (PLC). Two control systems were developed, and their performance were compared to that of a PI controller.

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A design procedure and experimental implementation of a PID controller was also presented by Situm *et al*. [7]. 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 [8] documented 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. Dumitriu [9] focused on the development of a MATLAB/SIMULINK library for servo-systems with friction as a part of a new simulation platform dedicated to model, analyse and control of friction. Guenther *et al*. [10] proposed a cascade controller with friction compensation based on the LuGre model. This control is applied to a pneumatic positioning system. The cascade methodology consists of dividing the pneumatic positioning system into two subsystems: a mechanical subsystem and a pneumatic subsystem.

In this paper, a Neural Network based intelligent PI controller is designed and simulated to increase the position accuracy in a pneumatic servo actuator. The pneumatic actuator consists of a proportional directional control valve

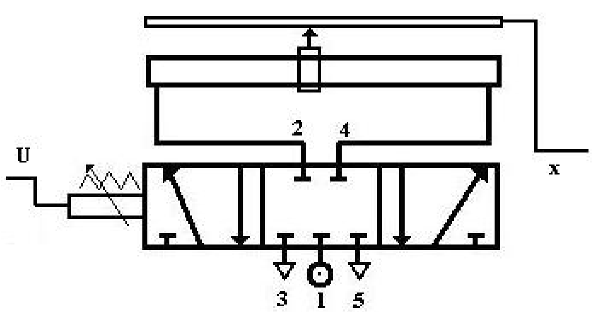

Fig. 1 The Schematic diagram of the servo pneumatic actuator.

connected with a pneumatic rodless cylinder. In this design, a well-trained Neural Network will provide the PI controller with suitable gains according to feedback that contains the changes in position error and the changes in external load force.

These gains should keep the resulting position control within minimum overshoot, minimum rise time and minimum steady state error.

II. NONLINEAR SYSTEM MODEL OF THE PNEUMATIC ACTUATOR

The complete mathematical model of the pneumatic servo actuator is obtained from the model of the pneumatic proportional directional control valve, then modelling the mass flow rate by analysing the thermodynamic changes in pneumatic cylinder and by applying Newton's second law of motion. It will be assumed time delays in the pneumatic pipes are neglected. Fig. 1 shows the schematic diagram of the servo pneumatic actuator. We used SIMULINK\MATLAB package and implemented the block diagram of the nonlinear mathematical model of the pneumatic rodless cylinder controlled by a directional control valve as shown in Fig. 2.

A. Modelling of proportional directional control valve

Most of proportional directional control valves consist of four main parts: proportional solenoid, housing with the control spool, positioning transducer and integrated analogue device. The control spool shifts left or right proportionally to the input signal on the solenoid. The positional transducer, which sends a signal to the integrated control device, measures the stroke of the spool, where it is compared to the reference value and a correct command signal now controls spool movement. In this way, the proportionality of the airflow with the command signal is ensured with considerable accuracy as mentioned by [11].

However, assuming the solenoid inductance is neglected, the relationship between control spool movement (x_{sp}) and the voltage input (u) is:

$$x_{sp} = C_V u \tag{1}$$

where (C_V) is the valve constant. Assuming the effective area of the valve orifice is (A_V), the relationship between the control spool movement and the effective area of the valve as mentioned by [11] is:

$$A_V \approx X_{sp}^2 . \frac{\pi}{4} \tag{2}$$

Valve areas for input and exhaust paths versus the spool displacement are changed according to the position of the spool. The direction of flows in cylinder chambers has opposite signs, when one chamber is charged the other chamber is discharged, thus the role of calculating the effective area of the valve should be switched for the second chamber as mentioned by [12].

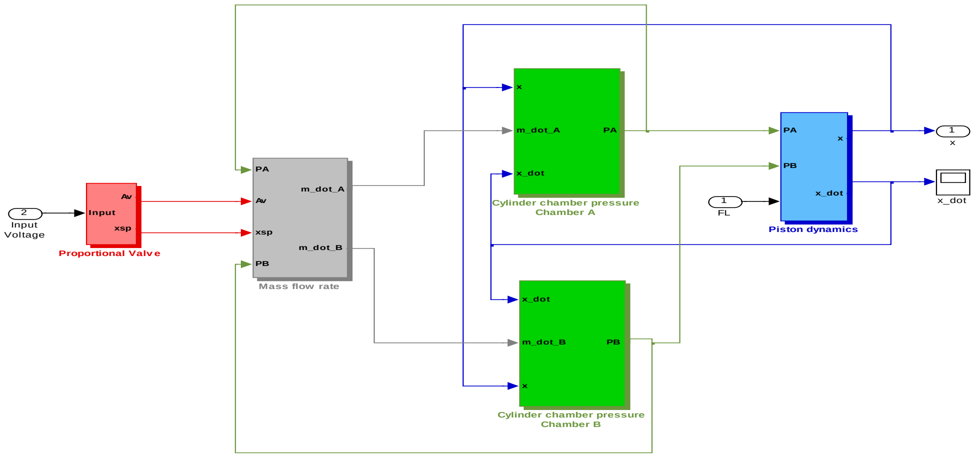

Fig. 2 Simulation model of Nonlinear mathematical model of the servo pneumatic actuator.

B. *Modelling of mass flow rate:*

Assuming isothermal process, (temperature is constant), the rate of change of pressure as mentioned by [2] is:

$$\dot{P} = \frac{R.T}{V}(k.\dot{m}_i - k.\dot{m}_o) - k.\frac{P}{V}\dot{V} \tag{3}$$

where $\dot{m}_i$ and $\dot{m}_o$ are input and output mass flow rates respectively, k is the heat ratio, V is the control volume and R is the gas constant.

By setting the origin of piston displacement at half of the cylinder length, the control volume (V) is:

$$V = A.(\frac{L}{2} \pm x) \tag{4}$$

Where A is the useful piston area, L is the piston stroke and x is the piston position. By substituting (4) in (3), the rate of change of pressure in the cylinder chambers is:

$$\dot{P} = \frac{R.T}{A.(\frac{L}{2} \pm x)}(k.\dot{m}_i - k.\dot{m}_o) - k.\frac{P}{A.(\frac{L}{2} \pm x)}(\pm A.\dot{x}) \tag{5}$$

where $\dot{x}$ is the rate of change of piston's position. However, the mass flow rate ($\dot{m}$) of the compressible gas through a valve orifice (A_V) is given by:

$$\dot{m}(P_u, P_d) = \begin{cases} C_f.A_V.C_1.\dfrac{P_u}{\sqrt{T}} & if\ \dfrac{P_d}{P_u} \le P_{cr} \\ C_f.A_V.C_2.\dfrac{P_u}{\sqrt{T}}\left(\dfrac{P_d}{P_u}\right)^{\frac{1}{k}}.\sqrt{1-\left(\dfrac{P_d}{P_u}\right)^{\frac{k-1}{k}}} & if\ \dfrac{P_d}{P_u} > P_{cr} \end{cases} \tag{6}$$

where (C_f) is a non-dimensional discharge coefficient, (P_u and P_d) are the upstream and downstream orifice pressures respectively, T is the orifice upstream temperature and (P_{cr}) is the critical pressure ratio. The constants C_1 and C_2 are given below:

$$C_1 = \sqrt{\frac{k}{R}.\left(\frac{2}{k+1}\right)^{\frac{k+1}{k-1}}} \text{ and } C_2 = \sqrt{\frac{2.k}{R.(k-1)}}\ .$$

The meaning of the upstream and downstream pressures is different for the charging and discharging process of the cylinder chamber. For charging, the pressure in the supply tank should be considered the upstream and the pressure in the cylinder chamber is the downstream one. For discharging process, the pressure in the chamber is the upstream and the ambient pressure is the downstream pressure as mentioned in [1]. Thus, the air in the valve flows through the input and output paths according to the following functions:

$$\dot{m}_{IA} = \dot{m}(P_S, P_A) \tag{7}$$

$$\dot{m}_{OA} = \dot{m}(P_A, P_a) \tag{8}$$

$$\dot{m}_{IB} = \dot{m}(P_S, P_B) \tag{9}$$

$$\dot{m}_{OB} = \dot{m}(P_B, P_a) \tag{10}$$

where $\dot{m}_{IA}$ and $\dot{m}_{IB}$ are the input mass flow rate in chambers A and B respectively, ($\dot{m}_{OA}$) and ($\dot{m}_{OB}$) are the output mass flow rate in chambers A and B respectively, (P_A) and (P_B) are the pressures in chamber A and B respectively, (P_a) is the atmospheric pressure and (P_S) is the supply pressure.

C. *Newton's second law of motion:*

Using Newton's second law of motion, the mechanical equation of the pneumatic actuator is:

$$M.\ddot{x} = (P_A - P_B).A - F_f - F_L \tag{11}$$

where M is the piston and load mass, F_f is the friction force and F_L is the external load force. The friction is presented by the following more general description static model as mentioned in [9]:

$$F_f = \begin{cases} F(v) & if & \dot{x} \neq 0 \\ F_L & if & \dot{x} = 0\, and\, |F_L| < F_S \\ F_s.\text{sgn}(F_L) & otherwise & \dot{x} = 0\, and\, |F_L| > F_S \end{cases} \tag{12}$$

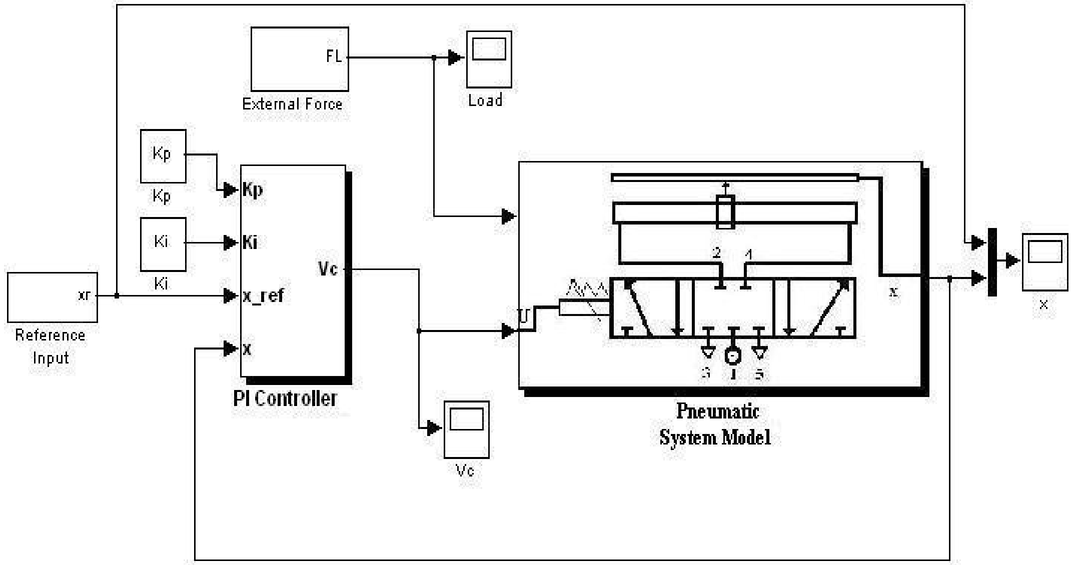

Fig. 3 Closed loop PI controlled pneumatic system.

Where $F(v)$ is an arbitrary function and F_S is the static friction. The arbitrary function can be represented by a Stribeck nonlinear function as mentioned by [9]:

$$F(v) = F_C + (F_S - F_C).e^{-\left(\dot{x}/\dot{x}_\delta\right)^{\delta_s}} + B.\dot{x} \qquad (13)$$

Where F_C is Coulomb friction, $\dot{x}_\delta$ is the Stribeck speed, B is the viscus friction coefficient and δ_S is the Stribeck exponent. This model allows a good representation of stick-slip motion behaviour and efficient simulations. The block diagram shown in Fig. 2 consists of five sub-blocks which implement the bulk of equations described in section-2. For example, the simulation of pressure in cylinder chambers A and B is modelled using (3) through (5). The simulation model implements pressure calculations in cylinder chambers A and B in a similar way except that the signs of x and $\dot{x}$ are complemented. The piston dynamics are simulated using (11) through (13).

III. NEURAL NETWORK BASED PI CONTROLLER

In order to increase the robustness of PI controller, a Neural Network based intelligent PI controller is used. In this approach, a well-defined Neural Network provides online the PI controller with appropriate gains 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, input patterns that contain the above mentioned parameters under different operating conditions are used and output patterns that contain the optimal values of gains are collected from several simulations of the closed loop PI controlled servo pneumatic actuator. Selection of gains is done by a certain performance index (PF); i.e. the K_P and K_I that makes PF minimum is the optimal PI gain with respect to each input vector (Error and F_L) as mentioned in [13]. These patterns are used to train the Neural Network and the output of the Neural Network will be optimal values of Proportional gain (K_P) and Integral gain (K_I).

In this work, the performance index is selected to minimize the overshoot, rise time and steady state error of the cylinder position response according to the following equation:

$$PF = Overshoot * \mathbf{K_1} + Rise\ time * \mathbf{K_2} + Steady\ \textbf{state}\ error * \mathbf{K_3} \qquad (14)$$

where K_1, K_2, and K_3 are weighting factors chosen to be 20, 80, and 100 respectively.

Details of the selection algorithm and the procedure of implementation are explained in [13].

IV. SIMULATION RESULTS

In order to simulate the servo pneumatic actuator model, it will be assumed that the actuator model consists of a pneumatic rodless cylinder (SMC CDY1S15H-500) with stroke length L=500 mm and diameter d=15 mm. Linear motion of the piston is controlled with a proportional directional control valve (FESTO MPYE-5 1/8 HF-010B), which is connected to both cylinder chambers. The valve has a neutral voltage for 5V control voltage and the input voltage is within the range of 0 to 10V. Table I gives specifications of the servo pneumatic system used in this paper as mentioned in [2] and referred to in other works [7],[8],[12]. The PI controlled pneumatic system model is shown in Fig. 3 and the Neural Network based PI controller together with the Pneumatic system is shown in Fig. 4.

A reference input voltage is applied to the pneumatic system model in the range between 0 to 10V and the piston position and piston speed responses are shown in Fig. 5. It can be noticed that the piston did not move till the voltage increased more than 5V, which is the neutral voltage of the solenoid. The results we obtained are in agreement with experimental and simulation results that were mentioned in [2].

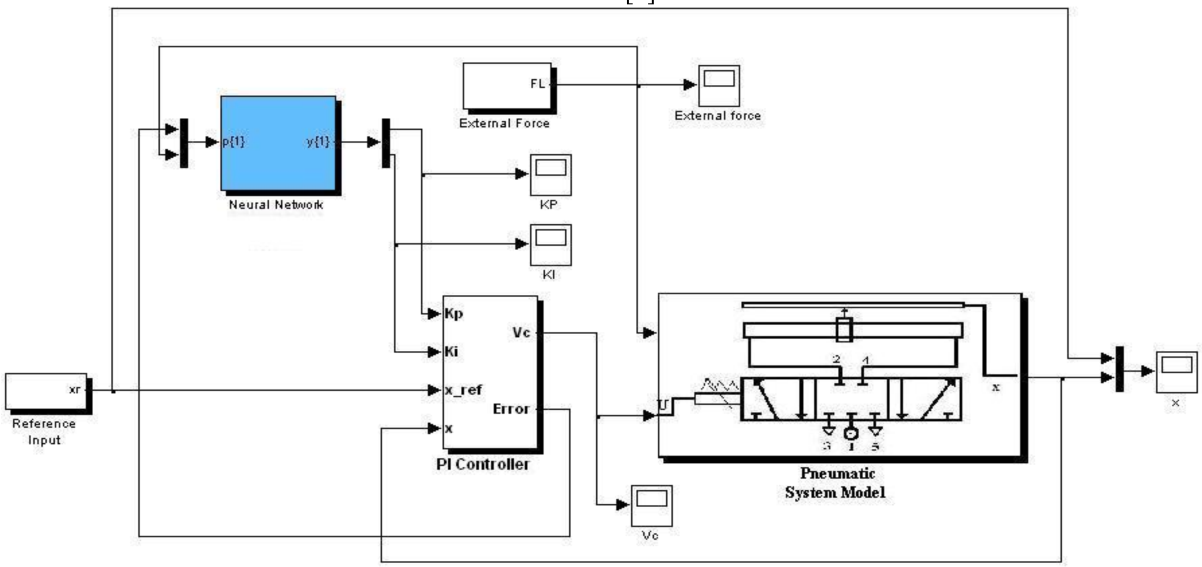

Fig. 4 Block diagram of the Neural Network based intelligent PI controlled pneumatic system.

Tan-Sigmoid activation functions are used in the hidden layers whereas linear activation functions are used in the output layer. The error in position and external load force are divided into intervals where error in position is chosen within the range of (-0.5) to (0.5) in steps of 0.01 and the external load force is chosen within the range of 1 to 10 N in steps of 1 N. Furthermore, KP and KI are limited within the range of (1) to (100). Using a SIMULINK model of pneumatic actuator, the PI controlled pneumatic system model shown in Fig. 3 is used to collect patterns of training. Using the above mentioned intervals, several simulations were done with the help of (14) and a total of 1111×4 input-output patterns are collected. By using *gradient-descent* with momentum back-propagation algorithm with a learning rate of 0.001 and momentum constant of 0.9, a Neural Network is trained after 250,000 epochs and SIMULINK Neural Network block diagram is eventually generated. Finally, this Neural Network SIMULINK block is connected with a 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. 4.

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, minimum rise time and minimum steady state error. The responses of the position of cylinder, the reference position input and the error in position are shown in Fig. 6. The Neural Network reads the error in position and the values of external load force and recalls the optimal values of KP and KI to keep the position response of the cylinder within the required performance as can be shown in Fig. 7.

In order to test the controller under the effect of variable load force, by applying a reference position input and an external variable load force at the same time to the pneumatic system model, responses of the position of cylinder, the reference position input and the error in position are shown in Fig. 8. It can be noticed that the controller tries to keep the position of the cylinder with minimum position error in spite of the effect of changing load force. Responses of changing the parameters of the controller and the shape of external load force are shown in Fig. 9. We compare this type of controller with a conventional type of PI controlled pneumatic system shown in Fig. 3. By applying the same reference input and external load force and tuning the parameters of the controller using trial and error to obtain cylinder position response with minimum overshoot, minimum rise time and minimum steady state error. It was found that the best values of KP and KI were (100) and (50) respectively. However, by setting parameters of the controller with the best values of gains, responses of position of cylinder, reference position, error in position and external load force are shown in Fig. 10.

A comparison between the two results, shown in Fig. 9 and Fig. 10, shows that the conventional PI controller fails to keep the cylinder position within the allowed minimums of overshoot and steady state error as the intelligent controller did. The cylinder keeps jittering even when the cylinder position reached the required value. 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 intelligent controller has the potential to compensate for the nonlinearities.

V. CONCLUSIONS

In this paper, a Neural Network based intelligent PI controller was designed and simulated to increase the position accuracy in a pneumatic servo actuator. The pneumatic actuator consists of a proportional directional control valve connected with a pneumatic rodless cylinder.

In this design, a well-trained Neural Network provides the 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 position within minimum overshoot, minimum rise time and minimum steady state error. These characteristics are satisfied without and with the effect of applying external variable load force.
A comparison between using Intelligent PI type of controller and conventional PI type shows that the position of cylinder using a conventional PI controller keeps jittering in an oscillating way when the position of cylinder reaches a steady state position value. This is because of nonlinearities that exist in the pneumatic actuator and yet the jittering does not happen when a Neural Network based Intelligent PI controller is employed.

REFERENCES

[1] W. Bolton, *Pneumatic and Hydraulic Systems*. Britain: Butterworth and Heinemanm Inc, 1997.
[2] Z. Šitum, D. Kosić, and M. Essert, "Nonlinear mathematical model of a servo pneumatic system," *9th International research / Expert Conference, TMT*, Antalya: Turkey, 26-30 Sept 2005.
[3] E. Richer and Y. Hurmuzlu, "A high performance force actuator system Part-2: Nonlinear controller design," *ASME Journal of Dynamic Systems Measurement and Control,* vol. 122, no. 3, Sept. 2000, pp. 426-434.
[4] X. Wang, Y. Cheng, and W. Sun, "Multi-step predictive control with TDBP method for pneumatic position servo system," *Transaction of the Institute of Measurement and Control*, 2006, pp. 28-53.
[5] P. L. Andrighetto, A. C. Valdiero, and L. Carlotto, "Study of the friction behaviour in industrial pneumatic actuators," *Proceedings of 18th international Congress of Mechanical Engineering (COBEM),* Ouro Preto, Brazil, Nov. 6-11 2005.
[6] M. B. Thomas, "Advanced servo control of a pneumatic cctuator," *Ph. D. dissertation*, *Ohio State University*, Ohio: USA, 2003.
[7] Z. Situm, D. Pavkovic, and B. Novakovic, "Servo pneumatic position control using fuzzy PID gain scheduling," *Transaction of the ASME*, vol. 126, June 2004, pp. 376-387.
[8] N. Sepehri and M. Karpenko, "Design and experimental evaluation of a nonlinear position controller for a pneumatic actuator with friction," *Proceeding of the 2004 American Control conference,* Boston: USA, June 30- July 2004, pp. 5078-5083.
[9] T. Dumitriu, "Development of a SIMULINK Toolbox for friction control design and compensation," *The annals of "Dunarea De Jos" University of Galati, FASCICLE III*, *ISSN 1221-454X*. Romania, 2005, pp. 5-10.
[10] R. Guenther, E. C. Perondi, E. R. DePieri, and A. C. Valdiero, "Cascade Controlled Pneumatic Positioning System With LuGre Model Based Friction Compensation," *Journal of the Brazil Society of Mechanical Science and Engineering* XXVIII, vol. 1, Jan-March 2006, pp. 48-57.
[11] Z. Šitum., D. Kosić, and M. Essert, "Modelling and control of servo pneumatic-drive," *Strojarstvo*, vol. 43, no. 1-3, 2001, pp. 29-39.
[12] E. Richer and Y. Hurmuzlu, "A High Performance force actuator system, Part-1 Nonlinear mathematical model," *ASME Journal of Dynamic Systems Measurement and Control*, vol. 122, no. 3, Sept. 2000, pp. 416-425.
[13] G. L. Wang, C. T. Fong, and K. L. Chang, "Neural-Network based self tuning PI controller for precise motion of PMAC motor," *IEEE trans. On Industrial Electronics*, vol. 48, no. 2, April 2001, pp. 408-415.

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Table I: Values of the system parameters

System Parameter	Value
Piston cross-section area	$A=1.767.10^{-3}$ m^2
Maximum effective area of valve	$Avmax=7.83.10^{-6}$ m^2
Viscus friction coefficient	B=65 Ns/m
Valve coefficient of discharge	$C_f=0.7$
Valve constant	$C_V=3.15745.10^{-4}$ m/V
Cylinder diameter	$d=15.10^{-3}$ m
Stribeck exponent	$\delta_S=2$
Coulomb friction	$F_C=24$ N
External load force acting on the piston	$F_L=0$ N
Static friction	$F_S=35$ N
Specific heat ratio of air	k=1.4
Cylinder stroke length	$L=500.10^{-3}$ m
Total mass of Piston, rods and load	m=1.91 kg
Critical pressure ratio	$P_{cr}=0.528$
Supply pressure	$Ps=5.10^5$ Pa
Gas constant	R=287
Air temperature	T=294.5 K
Stribeck speed	$\dot{x}_S=4.10^{-3}$ m/s

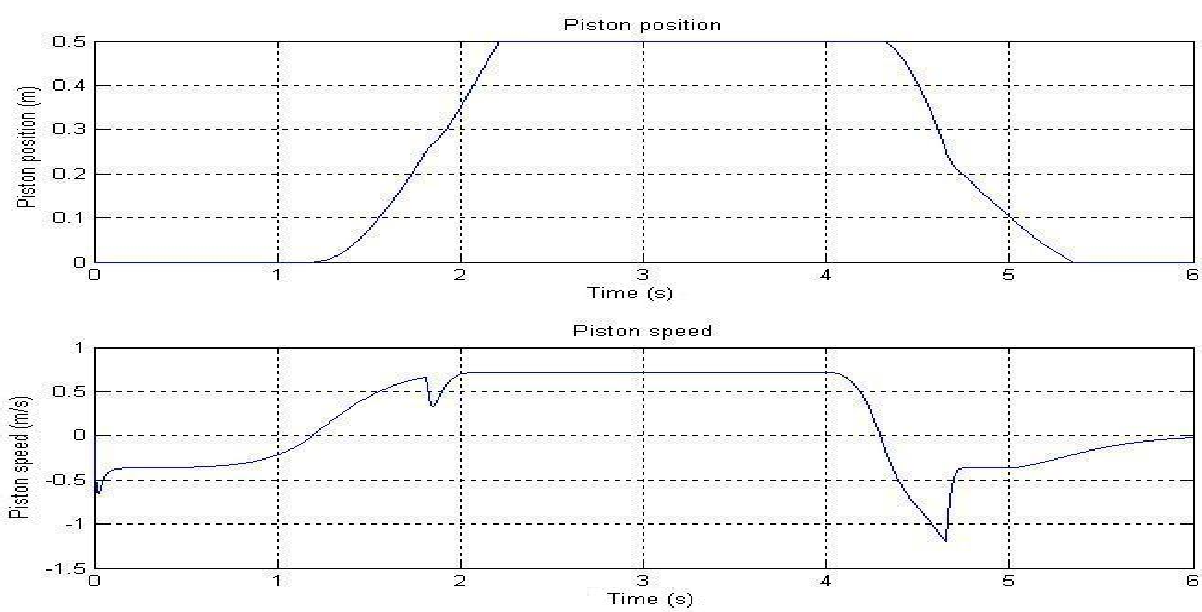

Fig. 5 Open loop responses of cylinder's position and speed.

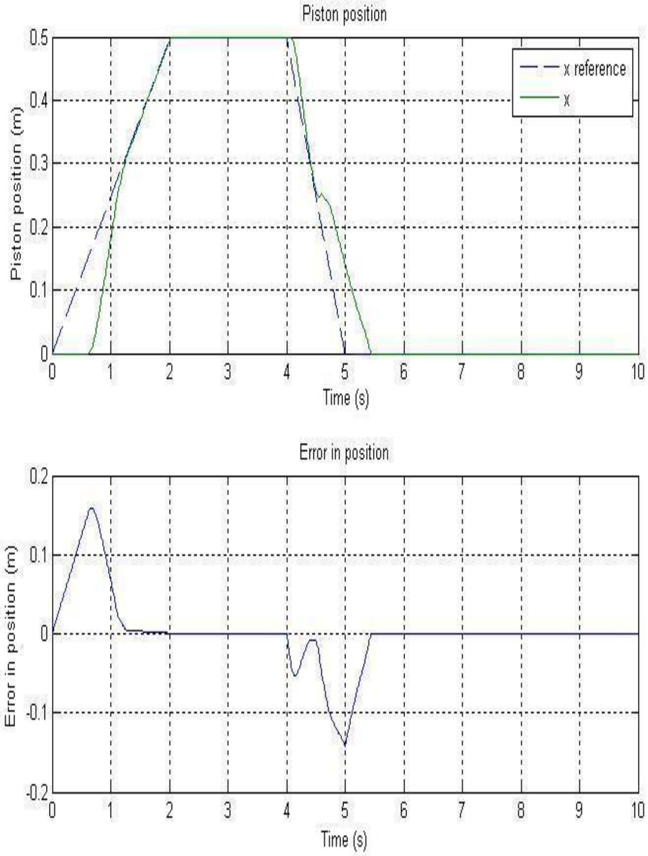

Fig. 6 Closed loop no-load piston position and error in position responses of Neural Network based PI controlled pneumatic system.

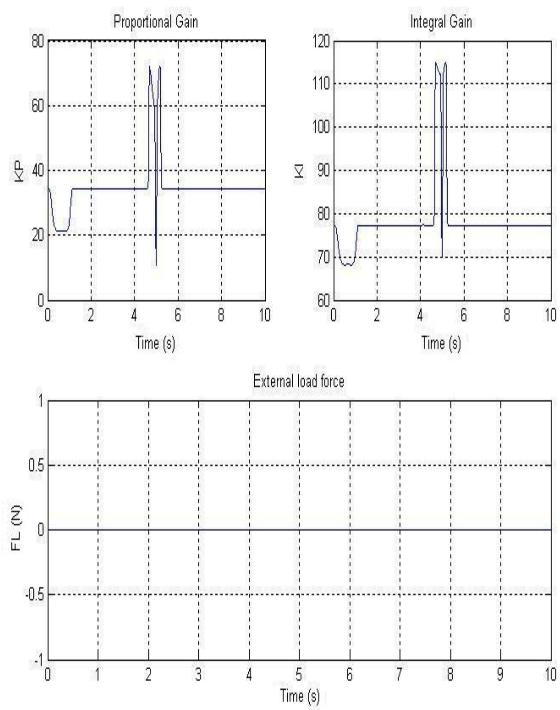

Fig. 7 Closed loop no-load K_P, K_I and F_L responses of Neural Network based PI controlled pneumatic system. based PI controlled pneumatic system.

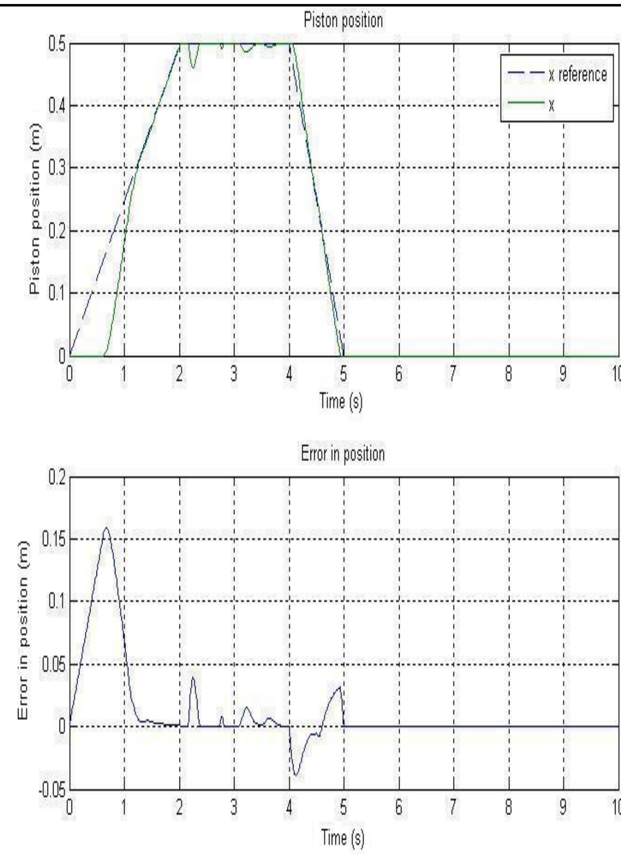

Fig. 8 Closed loop variable-load force piston position and error in position responses of Neural Network

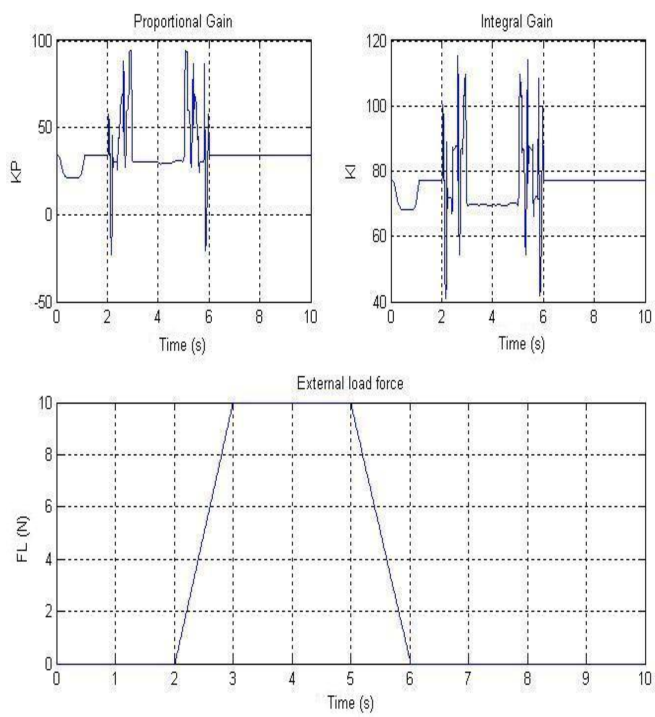

Fig. 9 Closed loop variable-load force K_P, K_I and F_L responses of Neural Network based PI controlled pneumatic system.

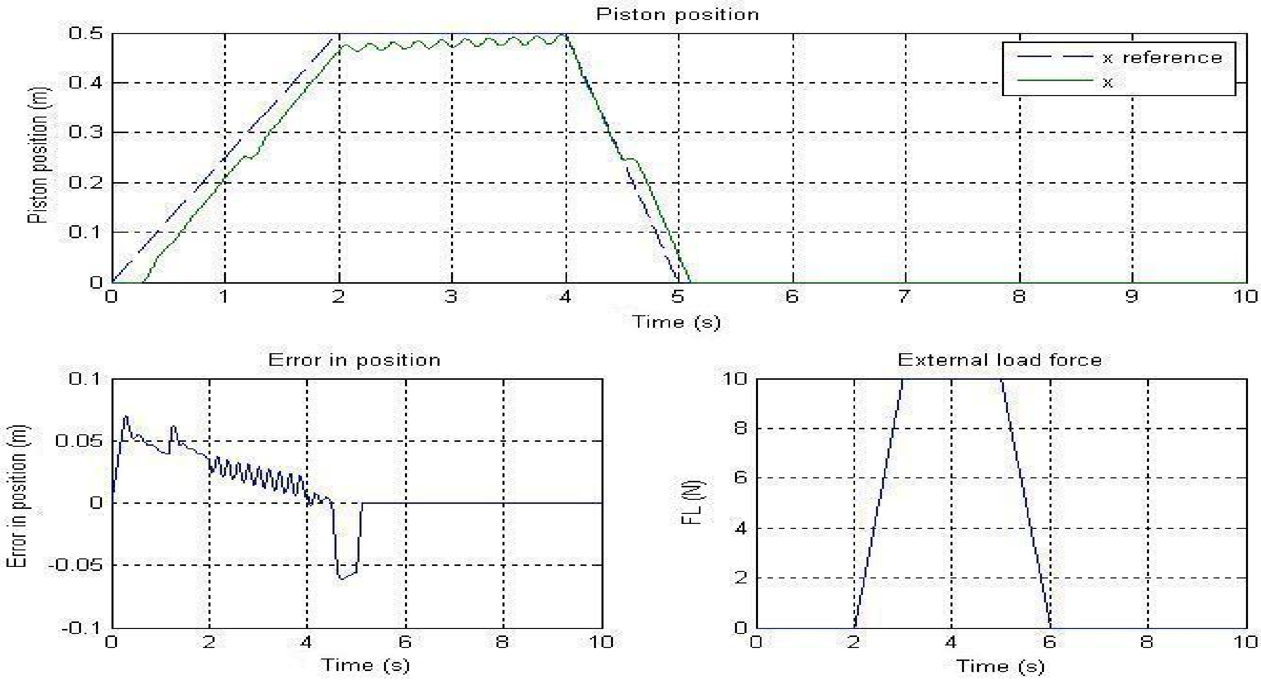

Fig. 10 Closed loop variable-load force responses of PI controlled pneumatic system.