MODELLING AND CONTROL OF PROPORTIONAL DIRECTIONAL CONTROL VALVE USING NEURAL NETWORK

Dr. Mohammed Y. Hassan * **Dr. Majid A. Aliewe***

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Abstract

A multi-layer, multi-input/ multi-output feed-forward back propagation neural network will be used to identify the model of proportional directional control valve with the addition of its nonlinearities. An electro-hydraulic training test bench is used to collect data for training the neural network. Using MATLAB, SIMUILNK the electro-hydraulic controlled system is tested, by applying a variable reference stroke position. A PI controller is tuned to get a stroke response with minimum overshoot and minimum steady state error. Modeling results were very satisfied and were very close to the experimental one with an error less than 10^{-10}. This work can be generalized by applying the same idea to any nonlinear valve.

Keywords: Neural Networks, Proportional Valve, Hydraulic System

الخلاصة

تم في هذا البحث أستخدام شبكه عصبيه متعددة الطبقات ومتعددة المداخل والمخارج ذي تغذيه أماميه وبطريقة الأمتداد العكسي لغرض نمذجة موديل رياضي خاص بصمام سيطره أتجاهي متناسب مع الأخذ بتظـر الأعتبار خواصه الاخطيه . لقد تم أستخدام منضدة فحص تدريبيه لمنظومه كهرو- هيدروليكيه لغـرض جمـع البيانات والتى من ثم سوف تستخدم لتدريب الشبكه العصبيه . لقد تـم بأسـتخدام برنـامج ال MATLAB, SIMULINK في بناء و فحص منظومة السيطره عن طريق تسليط موقع ضربه مرجعي متغير . تم تنغـيم المسيطر المتناسب-المتكامل للحصول على مواصفات أنتقاليه للضربه بأقل تجاوز للهدف وأقل خطأ مـستقر . ولقد كانت نتائج النمذجه مقنعه وقريبه من النتائج العمليه بمعدل خطأ أقل من 10^{-10} . أن هذا العمل يمكن تنفيذه بصوره عامه بتنفيذ نفس فكرة النمذجه على أي صمام غير خطي .

*Control and Systems Engineering Dept. University of Technology Baghdad, Iraq

Nomenclature

A_p : Active area of piston annulus, m^2
B : Bulk modulus, N/m^2
$dV_{A,B}$: Rate of change of volume of chamber A, B, m^3/s
F_{co} : Coulomb friction coefficient, N
F_{vo} : Viscous friction coefficient, N/m/s
K_L : Load stiffness, N/m
K_P : Proportional gain of PI controller
K_I : Integral gain of PI controller
K_{trans} : Displacement transducer constant, V/m
M_p : Mass of actuator piston and load, Kg
P_s : Supply pressure from hydraulic pump, Pa
$P_{A,B}$: Oil pressure in actuator port A, B, Pa
P_L : Load pressure, Pa
P_T : Tank pressure, Pa
$Q_{A,B}$: Oil flow at valve control port A, B, m^3/s
Q_L : Total oil flow though the load, m^3/s
Q_{pump} : Maximum oil flow capacity of pump, m^3/s
x : Total stroke of piston, m
V_t : Volume of trapped oil between pump and valve, m^3
U_c : Output controlled voltage to valve, V
U_r : Command Reference, V
U_x : Output of displacement transducer, V
U_{max} : Maximum controller output voltage, V

1-Introduction

Hydraulic systems are widely employed in many industrial applications due to their ability to Economically convert mechanical energy into fluid energy. It can be regulated to provide speed, force, and direction of control with the help of some simple components. It is used in industry like construction, aircraft, mining, …etc.

However, hydraulic systems provide high force requirements with considerably greater power/weight ratio than other power transmission systems. No other type of power transmission system provides the range of control over speed, force and direction that could be obtained through fluid power. Although, hydraulic systems include various nonlinearities in static and dynamic characteristics of their components. Consequently, a variety of nonlinear phenomena occur in the system.

In the context of hydraulic servo systems, flow control valves fall broadly into two main categories: proportional valves and servo valves. Proportional valves use direct actuation of the spool from an electrical solenoid or torque motor. Whereas servo-valves use at least one intermediate hydraulic amplifier stage between the electrical torque motor and the spool.

When modeling complex servo-valves, it is sometimes possible to ignore any inherent nonlinearities and employ a small perturbation analysis to derive a linear model which approximate the physical system. Such models are often based on classical first or second order differential equations. So, in order not to lose accuracy, it is necessary to model the servo-valve dynamics as a nonlinear model [8].

Many researchers deal with the modeling and control of hydraulic systems. Papadopoulos [6] focused on modeling and parameter estimation of electro-hydraulic actuation system of an articulated forestry machine. Barton et al. [1] presented a simple method to estimate the parameters of a proportional valve such as spring constant, while Vaughan and Gamble [10] presented linear models of various configurations of control valves and hydraulic linear models of proportional valves. Furthermore, the fundamental smooth nonlinearity which arises from geometric imperfections of the valve and spool in hydraulic valve model was described by Margolis and Hennings [3]. Moreover, Norgaard [4] discussed the linear modeling of hydraulic actuator that is used for controlling the position of a carne arm. Also, Schwartz [9] proposed a nonlinear model which includes the physical phenomena that exerts a significant influence on the performance of this hydraulic component, such as friction. Joshi [2] investigated the effects of servo valve nonlinearity, actuation compliance and friction related nonlinearity on the dynamics of a flight control surface, during its displacement through an electro-hydraulic actuation system.

It can be concluded that most of the researchers and designers of hydraulic systems had chosen one particular type of modeling and control, depending on their machine type, applications and cost of the system. They supposed the hydraulic valve as a linear model type.

This paper studies the dynamic behavior of electro-hydraulic system. It also discusses the approach of using a neural network to model a nonlinear Proportional Directional Control Valve (PDCV). This nonlinear model can be used as a valuable tool in the analysis and control of electro-hydraulic actuation systems. Neural networks Toolbox of MATLAB package will be used to train the neural network. SIMULINK will be used to simulate the electro-hydraulic control system. This approach will be extended to be used to tune the controller of nonlinear electro-hydraulic valve. It includes manufacturing systems, materials test machines, active suspension systems, mining machinery, paper machines, injection molding machines, steel and aluminum mill equipment and flight simulation. Also, electro-hydraulic systems are common in aircrafts, where their high power-to-weight ratio and precise control make them an ideal choice for actuation of flight.

2- Modeling Of Electro-Hydraulic System

A typical position controlled electro-hydraulic system consists of a power supply, electronic controller, proportional directional control valve, linear actuator and displacement transducer, as shown in Fig. (1) [5]. The controller compares the signal from the feedback displacement transducer with a reference input to determine the position error, and produces a command signal to drive the control valve. The control valve adjusts the flow of pressurized oil to move the actuator until the desired position is attained. A SIMULINK model of the position controlled electro-hydraulic is shown in Fig. (2), The model consists of sub-models that represent the elements of position controlled electro-hydraulic system , as follows:

2-1 Hydraulic Power Supply

All hydraulic systems require a supply of pressurized fluid, usually a form of mineral oil. The behavior of the hydraulic power supply may be modeled by applying the flow continuity equation to the volume of trapped oil between the pump and control valve. In this case, the input flow is held constant by the steady speed of the pump motor, and the volume does not change. The equation of the model is [8]:

$$P_S = \frac{\beta}{V_t} \int Q_{pump} - Q_L)dt \qquad (1)$$

This equation takes into account the load flow (Q_L) drawn from the supply by the control valve, and accurately models the case of a high actuator slew rate resulting in a load flow which exceeds the flow capacity of pump. The action of the pressure relief valve may be modeled using a limited integrator to clamp the system pressure to the nominal value. However, the SIMULINK model of the hydraulic power supply is shown in Fig. (3).

2-2 Electronic Controller

The electronic controller continuously monitors the input reference input position (U_r) and compares it against the actuator position (U_x) measured by displacement transducer to yield error signal ($e= U_r-U_x$).

Most conventional electro-hydraulic servo-systems use a PI or PID controller. In this work, the aim is to reach the reference position with minimum steady state error. So, it will be assumed that a PI controller is used as an electronic controller. The equation of the controller in s-plane is [5]:

$$U_C(s) = K_P.E(s) + \frac{K_I}{s} \qquad (2)$$

where K_P and K_I are the proportional and integral constants of PI controller respectively. However, the SIMULINK of PI controller is shown in Fig. (4).

2-3 Linear Actuator

A hydraulic actuator is a device which converts the hydraulic energy into mechanical force or motion. Linear actuators are those with linear movement (sometimes called rams, cylinders or jacks). They may be divided into those in which hydraulic pressure is applied to one side of the piston only (single acting), and those in which pressure is applied to both sides of the piston (double acting), and therefore capable of controlling movement in both directions. Moreover, linear actuators may be classified as a single-ended or double-ended type. The model of the linear actuator is divided into two sub-systems:

2-3-1 Cylinder Chamber Pressure

The relationship between valve control flow and actuator chamber is important because the compressibility of the oil creates a spring effect in the cylinder chambers which interacts with the piston mass to give a low frequency resonance. The effect can be modeled using the flow continuity equation which relates the net flow into a container to the internal fluid volume and pressure [9]:

$$\sum Q_{in} - \sum Q_{ouy} = \frac{dV}{dt} + \frac{V}{\beta}\frac{dP}{dt} \qquad (3)$$

Equation (3) can be re-arranged to find the instantaneous pressure in chamber A as follows [8][9]:

$$P_A = \frac{\beta}{V_t} \int Q_A - \frac{dV_A}{dt})dt \qquad (4)$$

This equation can also represent chamber B. The SIMULINK of chamber A or B is shown in Fig. (5).

2-3-2 Piston Dynamics

The net force acting on the piston (F_P) can be computed by multiplying the area of the piston annulus (A_P) by the differential pressure between two chambers A and B [8]:

$$F_P = (P_A - P_B).A_P \qquad (5)$$

By applying Newton's second law, an equation of forces for piston motion can be established. It will be assumed that the piston delivers a force to a linear spring load with stiffness (K_L), which will allow us to investigate the load capacity of the actuator. The effect of friction between the piston and oil seals at the annulus and end caps is also included. The total friction force depends on piston velocity, driving force (F_P), oil temperature and possibly piston position. One method of modeling friction is as a function of velocity, in which the total frictional force is divided into static friction, Coulomb friction and viscous friction. Assuming that the viscous and Coulomb friction components dominate, equation of force will be [8][9]:

$$F_P = M_P.\frac{d^2x}{dt^2} + F_{VO}.\frac{dx}{dt} + F_{CO}.\text{sign}(\frac{dx}{dt}) + K_L.x \qquad (6)$$

where viscous and Coulomb friction coefficients are denoted by F_{VO} and F_{CO} respectively. It will be assumed in this model that the leakage effects are neglected. The SIMULINIK model of piston dynamics is shown in Fig. (6).

2-4 Displacement Ransducer

Position transducers are usually used with the actuator. The transducer is often attached directly to the piston rode. Various types of feedback transducer are in use, including increment or absolute encoders, LVDT, and RVDT. In industrial applications employing linear displacement control, the LVDT is a common use of feedback transducer due to its accuracy and robustness [8]. The conversion factor of the transducer is assumed to be a constant (K_{trans}).

2-5 Modelingof Roportional Control Valve

A major advantage of proportional valves is that they are unaffected by changes in supply pressure and oil viscosity. However, the relatively large armature mass and large time constant associated with the coil means that these valves generally have poor dynamic performance compared with servo-valves of equivalent flow characteristics. In recent years, "servo-proportional" valves have begun to appear with shorter spool displacements and lighter spools, giving dynamic performance which approaches that of true servo-valves but much lower cost.

In many advanced control schemes, it is necessary to have a mathematical model of the valve in order to define an appropriate control algorithm. Central on the modeling process is the measurement or assignment of the valve parameters or coefficient values. The manufacturer can often specify some of the parameter values such as spring constants, spool mass, spool areas, …etc. However, friction, flow reaction force, and spool metering area values,…etc, are very difficult to define or measure and must be approximated in some fashion [1].

Neural networks are computational models of the brain. There are many types of neural networks representing the brain's structure and operation with varying degrees of sophistication. Neural networks consist of a number of inter connected processing units, (PEs), or neuron. How the inter-connections are arranged and the nature of the connections determine the structure of a network. How strengths of the connections are adjusted or trained to achieve a desired overall behavior of the network is governed by its learning algorithm.

One type of neural networks is the feed-forward neural network. In this type, the neurons are generally grouped into layers. Signals flow from input layer through to the output layer via unidirectional connections, the neurons being connected from one layer to the next, but not within the same layer.

However, the task of system identification is essentially to find suitable mappings which can approximate the mappings implied in a dynamic system. So, feed-forward neural networks can identify linear or nonlinear system models They are effective for identification of dynamic systems that are difficult for conventional theories to deal with. A number of highly nonlinear systems have been successfully identified by neural networks with sigmoidal nonlinear PEs [7]. When linear system is to be identified, only linear PEs are used in the neural network identifier, while nonlinear PEs are ádopted for the hidden layer of the neural network when the system to be identified is nonlinear.

In this paper, in order to identify the model of proportional directional control valve with the addition of its nonlinearities, a multi-layer, multi-input/ multi-output feed-forward back propagation neural network will be used. In order to model the nonlinearities of the valve, the PEs used in the hidden layer are taken to be hyperbolic tangent sigmoid, type, while the PEs of the output layer are of linear type. The inputs to the network are the supply pressure (P_S), control voltage (U_C), and pressures of chamber A and B (P_A and P_B), while the outputs of the neural network are the Oil flow at valve control ports A and B (Q_A and Q_B). In order to train the neural network, the Levenberg-Marquardt back propagation algorithm will be used. A general block diagram of the back propagation feed-forward neural network that represents the proportional directional control valve is shown in Fig. (7).

3-ExperimentalandSimulation Results

In order to implement the algorithm of modeling a proportional directional control valve using neural network, an electro-hydraulic training test bench of model type Hydroprax 2 prop is used. The valve used in this electro-hydraulic system is a PDCV of model type 4WRE6081X/24Z4M. This valve is controlled by an amplifier card of model type VT5003. The actuator used is of double acting, single-ended, linear type of model 70F40/25-300Z11/01HCDM11T. The photograph of the test bench is show in Fig. (8), while the schematic diagram of the system is shown in Fig. (9). Moreover, the details of the values of the parameters of the electro-hydraulic test bench are listed in Table (1).

To collect data that are needed to model the valve in the test bench, a constant P_S of $30*10^5$ pa was supplied by a hydraulic pump. The control voltage produced by the electronic amplifier (U_C) was changed within a range of (±6 V) and the values of (P_A , P_B Q_A) and (Q_B) where measured experimentally. Many tests where made with and without the addition of the weight (load). Every test was made many times and the data were averaged to get dependent measuring values. However, the characteristics of the valve which represent the relationship between the control voltage (Uc) Vs. the oil flow in valve (Q) is shown in Fig. (10). By using curve fitting done by MATLAB toolbox, the characteristics equation of the valve shown in figure is fitted to a 4th order nonlinear equation:

$$Q_{A,BC} = -3.9655*10^{-8}U_C^{-4} - 7.8825*10^{-8}U_C^{3} + 1.1987*10^{-6}U_C^{2} + 3.3127*10^{-5}U_C + 4.5143*10^{-5} \quad (7)$$

A MATLAB file was written that contains the measured data. A feed-forward neural network with one hidden layer was generated with the help of neural networks MATLAB toolbox. The activation functions of the hidden layer were taken to be hyperbolic tangent sigmoid, (tansig), type, while the activation functions of the output layer were taken to be a linear type, (purelin). Using trial and error, with the help of Levenberg-Marquardt back propagation algorithm, (trianlm), it was found that by selecting five nodes in the hidden layer with a learning rate of 0.05 and after 300 epochs, the neural network was trained with a training error of less than (10^{-10}). The trained neural network was simulated by applying an input data for the tests and draw the relationship between controlled voltage and oil flow in valve. The next step was by generating a SIMULINK sub-block that represents the neural network. This block was replaced by the proportional valve block shown in Fig. (2).

Using the same data of the elements of electro-hydraulic system mentioned in table (1), SIMUILNK of the electro-hydraulic controlled system was tested, by applying a variable reference stroke position of (0-0.1)m. Using trial and error, the PI controller was tuned to get a minimum overshoot with minimum steady state error. The best values were obtained to be K_P=450 and K_I=0.011. The responses of the stroke position and reference position are shown in Fig. (11). It can be shown from the figure that the steady state error is less than 0.3%. The PI controller tries to compensate the change in reference input by changing the controlled voltage as shown in Fig. (12). However, the change in controlled voltage will change the oil flow rate though the valve, and as a result the pressure in chambers A and B are changed as shown in Fig. (13).

4-Conclusions and Future Work

In this work the modeling of electro-hydraulic controlled systems were discussed. These systems were globally used in many industrial applications. In many advanced control schemes, it is necessary to have a mathematical model of the valve in order to define an appropriate control algorithm. However, there are many parameter values related to the valve that are very difficult to define or measure and must be approximated in some fashion.

In order to identify the model of proportional directional control valve with the addition of its nonlinearities, a multi-layer, multi-input/ multi-output feed-forward back propagation neural network was used. An electro-hydraulic training test bench was used to collect model data for training the neural network. Using neural network MATLAB toolbox, a feed-forward neural network with one hidden layer was generated. The SIMULNIK of the electro-hydraulic controlled system was tested, by applying a variable reference stroke position of (0-0.1)m.

The results of obtaining the neural network model were very satisfied and were very close to the experimental one since the error of training the neural network was less than 10^{-10}. A SIMULINK Sub-block of the neural network was generated. Furthermore, the SIMULINK of the electro-hydraulic controlled system with the addition of PI controller was built. The PI controller was tuned to get minimum overshoot and minimum steady state error (less than 0.3 %).

This work can be generalized by applying the same idea to any nonlinear valve. The person can do simple tests and collect the data that represents the valve. After that, the data are used to train the feed forward neural network. The trained neural network can be used as a nonlinear model of the valve.

In this model, the leakage effects were neglected. As a future work, to get a more accurate hydraulic model, the leakage effects must be added. Also, since these models are nonlinear, it is preferred to use an intelligent controller instead of a classical PI controller, such as fuzzy logic controller.

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Table (1) Data of Electro-hydraulic test bench.

Symbol	Value
A_p	$12.566*10^{-4}$
B	$1.8*10^{8}$
F_{co}	0.8
F_{vo}	300
K_L	1458.27
K_{trans}	1
M_p	25
P_s	$30*10^{5}$
Q_{pump}	$0.1666*10^{-3}$
x	0.3
V_t	$57.0045*10^{-6}$
U_{max}	±6

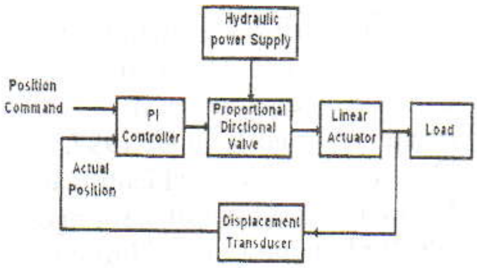

Fig. (1) Position controlled electro-hydraulic Systems.

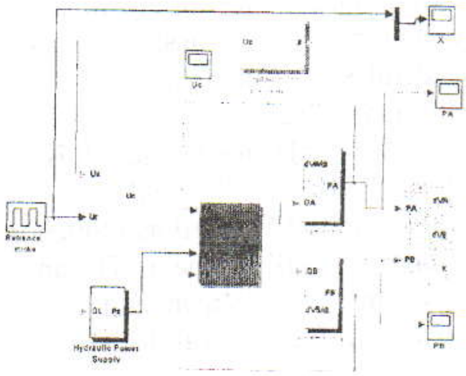

Fig. (2) SIMULINK model of Position controlled electro-hydraulic system.

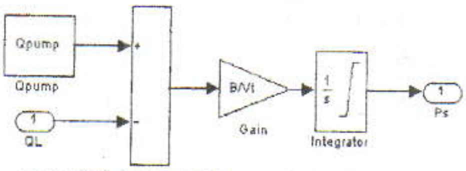

Fig. (3) SIMULINK model of hydraulic power supply.

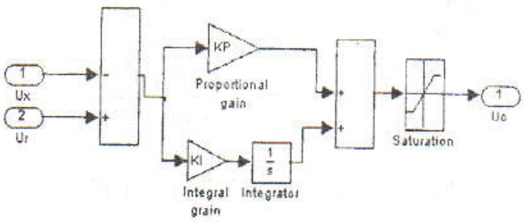

Fig. (4) SIMULINK of PI controller.

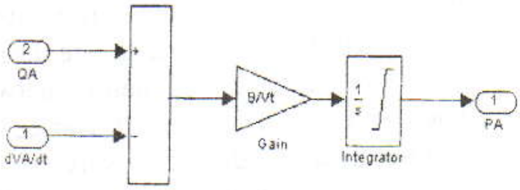

Fig. (5) SIMULINK model of Chamber A and B.

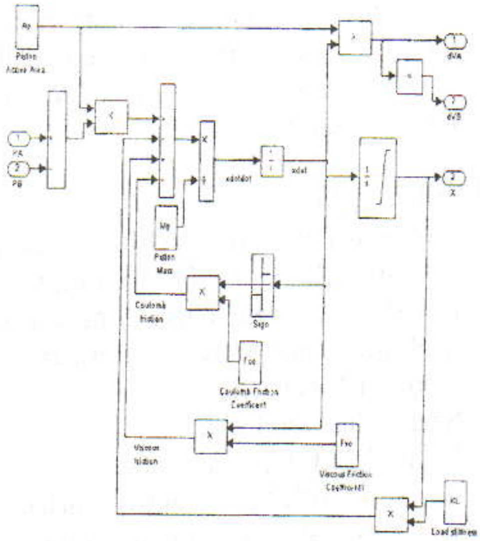

Fig. (6) SIMULINK model of piston dynamics.

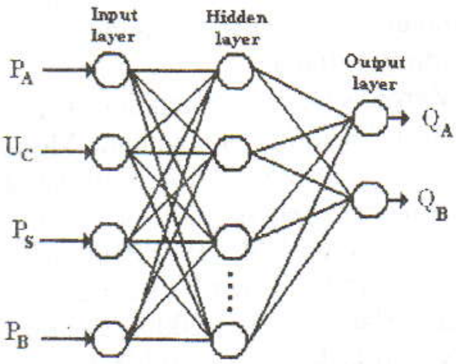

Fig. (7) General block diagram of feed-forward neural network valve model.

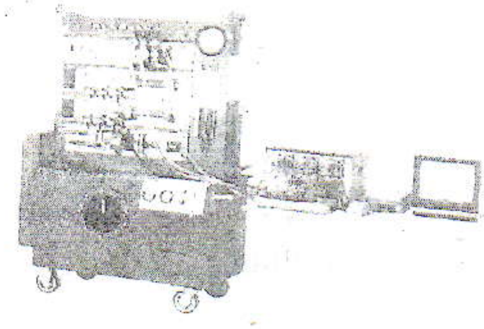

Fig. (8) Photograph of electro-hydraulic control unit test bench.

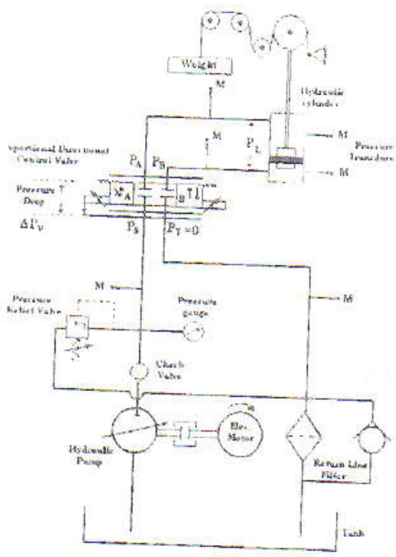

Fig. (9) Schematic diagram of electro-hydraulic control unit test bench.

Fig. (10) Characteristics of nonlinear valve (Uc Vs. Q).

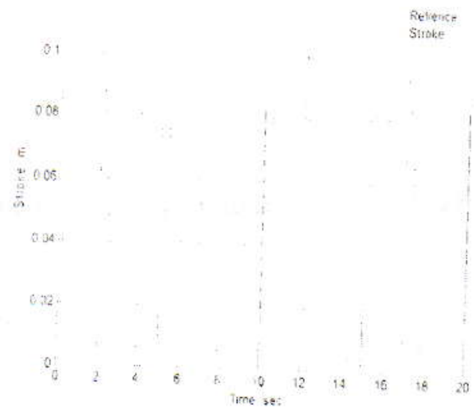

Fig. (11) Response of actuator Stroke.

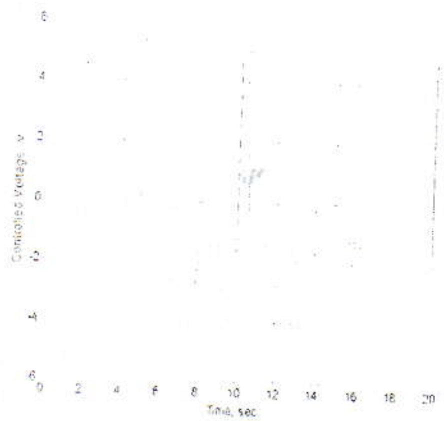

Fig. (12) Controlled voltage of PI controller.

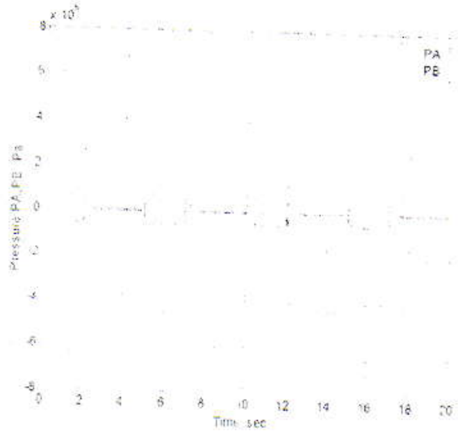

Fig. (13) Pressure in chamber A and B.