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Comparison Between Neural Network Based PI and PID Controllers

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Abstract—The 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, and in robotics; e.g. two-legged robot.

In this paper, a Neural Network based PI controller and Neural Network based PID controller are designed and simulated to increase the position accuracy in a pneumatic servo actuator. In these designs, a well-trained Neural Network provides these controllers 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 Neural Network based PI controller and Neural Network based PID controller was made to find the best controller that can be generated with simple structure according to the number of hidden layers and the number of neurons per layer. It was concluded that the Neural Network based PID controller was trained and generated with simpler structure and minimum Mean Square Error compared with the trained and generated one used with PI controller.

Index Terms— NeuralNetwork, PID, PI, Pneumatics

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 while pneumatic systems use a compressible fluid, usually air. 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, lightweight and good power to weight ratio, but due to the compressible nature associated with the fluid and the quick speed, it is 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 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 systems. Sepehri and Karpenko [5] 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. Guenther, Perondi et al. [6] 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 PI controller and A Neural Network based PID controller are designed and simulated to increase the position accuracy in a pneumatic servo actuator which consists of a proportional directional control valve connected with a pneumatic rodless cylinder.. A comparison between them is studied to find the best controller that can be generated with simple structure according to the number of hidden layers and the number of neurons per layer. In this design, well-trained Neural Networks will provide the PI controller and PID 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 modeling the mass flow rate by analyzing the thermodynamic changes in pneumatic cylinder and by applying Newton's second law of motion. 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 [7].

Fig. 1 The Schematic diagram of the servo pneumatic actuator

III. NEURAL NETWORK BASED PI and PID CONTROLLERS

The first step in this research is to increase the robustness of PI controller, a Neural Network based 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).

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

The aims are to study the capability of this approach to design a well trained Neural Network with minimum Mean Square Error (MSE) which tunes a PI, and also to study the capability of generating this Neural Network with simple structure according to the number of hidden layers and the number of neurons per layer.

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 according to 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 [8]. 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:

$$PF = \text{Overshoot} * K_1 + \text{Rise time} * K_2 + \text{Steady-state-error} * K_3 \quad (1)$$

where K_1 , K_2 , and K_3 are weighting factors chosen to be 20, 80, and 100 respectively. However, details of the selection algorithm and the procedure of implementation are explained in [8].

The second step in this research is to design a Neural Network based PID controller. The same previous algorithm is modified to design this type of controller. This controller assumes the value of Proportional gain is constant and can be found by using trial and error while the output of the Neural Network will be the optimal values of Derivative gain (K_D) and Integral gain (K_I). A well-defined Neural Network provides online the PID controller with appropriate gains according to the change in the previous selected operating conditions. However, it is mentioned that the same previous approach with the same performance index, equation (1), will

be used to collect the data in order to train this type of Neural Network.

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 0-10V. However, specifications of the servo pneumatic system used in this paper are mentioned in [7]. The PI controlled pneumatic system model is shown in Fig. 3.

A reference input voltage is applied to the pneumatic system model in the range between 0-10V and the piston position is shown in Fig. 4. 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 parameters of the pneumatic system model with respect to a reference voltage were measured. These include mass flow rates of chambers A and B, pressure in chambers A and B and effective area of solenoid etc. The results we obtained are in agreement with experimental and simulation results that were mentioned in [2],[7]. The first step is to design a Neural Network based PI controller, The error in position and external load force are divided into intervals where error in position is chosen within the range of $(-0.5, 0.5)$ in step of 0.01 and the external load force is chosen within the range of 1-10N in step of 1 N. Furthermore, K_P and K_I are limited within the range of (1-100). 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 Equation (1) and a total of 1111×4 input-output patterns are collected. A *gradient-descent* with momentum back-propagation algorithm is used to train the Neural Network for the collected patterns. Tan-Sigmoid activation functions are used in the structures of hidden layers of this neural network, whilst linear activation functions are used in the output layer. Different structures of this neural network were tested by simulation. These tests include the change in the number of hidden layers, number of nodes per hidden layer, learning rate and momentum constant to obtain a Neural Network with minimum MSE and simple structure. It is concluded after doing these simulation tests that the best Neural Network was trained after 210,000 epochs with a structure of two inputs, two hidden layers of 25 nodes for each layer and two outputs. The learning rate and the momentum constant were selected to be 0.001 and 0.9 respectively. The MSE was found to be

168.9. Finally, this generated 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. 5. As the reference position input with no external load force applied to the closed loop system, the controller tries to maintain the position of the cylinder follows 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 K_P and K_I 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.

The second step is to design of Neural Network based PID controller by modifying the PI controlled system, shown in Fig. 10, into PID controller. Several tests using trial and error were made to find the best value of K_P to achieve the required transient response under the effect of variable load force. It is found that the best value is (35). It will be assumed that K_I is limited within the range of (1-100) and K_D is limited within the range of (1-10).

Using the same previous mentioned intervals for error in position and external load force, a total of 1111×4 input-output patterns are collected. Using the same previous algorithm to select the Neural Network with minimum MSE and simple structure of PI controller, It was concluded after doing these simulation tests that the best Neural Network for tuning the PID controller was trained after 123000 epochs with a structure of two inputs, one hidden layer of 25 nodes and two outputs.

The learning rate and the momentum constant were selected to be 0.001 and 0.3 respectively. The MSE was found to be 19.41. Thus, SIMULINK block diagram of Neural Network is eventually generated and this Neural Network SIMULINK block is connected with a PID controller.

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; Fig. 11. Responses of changing the parameters of the controller and the shape of external load force are shown in Fig. 12.

Fig. 3 Closed loop PI controlled pneumatic system

Fig. 4 Open loop responses of cylinder's position

Fig. 5 Block diagram of the Neural Network based intelligent PI controlled pneumatic system

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

Fig. 8 Closed loop variable-load force piston position and error in position responses of Neural Network based PI controlled pneumatic system

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 Block diagram of the Neural Network based PID controlled pneumatic system.

Fig. 11 Closed loop variable-load force piston position and error in position responses of Neural Network based PID controlled pneumatic system

Fig. 12 Closed loop variable-load force K_D , K_I and F_L responses of Neural Network based PID controlled pneumatic system.

A comparison between the results of the two controllers concludes that the Neural Network based PID controller has a simpler structure and less MSE during training compared with a Neural Network based PI controller. This provides that the first controller recalls the output parameters with a time less than the second one. Also, the hardware implementation of the Neural Network based PID type is less complicated. Also, it can be noticed from the results that the output position of the Neural Network based PID type is less jittering in the steady state region compared with the output position for the Neural Network based PI type. This is because in the Neural Network based PID type we are changing the dynamic behavior of the closed loop system, by changing the integral and derivative gains of the controller, by changing the position of closed loop poles and zeros at the same time, whilst in the Neural Network based PI type we are changing the positions of the closed loop poles by changing the proportional and integral gains. This can be noticed from Fig. 9 and Fig. 12. The parameters of the Neural Network based PID controller (K_I and K_D) reached steady state values faster than the parameters of the Neural Network based PI controller (K_P and K_I). Although the Neural Network based Neural Network based PID controller has these advantages, the controller takes longer time to make the output of position follow the reference position compared with the one using Neural Network based PI type.

V. CONCLUSIONS

In this paper, a Neural Network based intelligent PI controller and Neural Network based PID controller were 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 these designs, a well-trained Neural Network provides the PI and the PID controllers 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 the Neural Network based PI type of controller and Neural Network based PID type shows that the Neural Network based PID type was designed with simpler structure according to the number of hidden layers and the number of neurons per layer as compared with the one that was designed with PI type. This gives the capability of implementing the Neural Network based PID controller with simpler hardware compared with the Neural Network based PI type. Also, the Neural Network that tunes the Neural Network based PID controller was trained with less MSE than

the value of the one for the Neural Network used in the Neural Network based PI type. This gives the fact that the first Neural Network was trained more accurate than the second one.

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