CONTROL OF A PNEUMATIC SYSTEM WITH ADAPTIVE NEURAL NETWORK COMPENSATION

BY

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Abstract


Considerable research has been conducted on the control of pneumatic systems due to their potential as a low-cost, clean, high power-to-weight ratio actuators. However, nonlinearities such as those due to compressibility of air continue to limit their accuracy. Among the nonlinearities in a pneumatic system, friction can have a significant effect on tracking performance, especially in applications that use rodless cylinders which have higher Coulomb friction than rodded cylinders.

Compensation for nonlinearities in pneumatic systems has been a popular area of research in pneumatic system control. Most advanced nonlinear control strategies are based on a detailed mathematical model of the system. If a simplified mathematical model is used, then performance is sensitive to uncertainties and parameter variations in the robot. Although they show relatively good results, the requirement for model parameter identification has made these methods difficult to implement. This highlights the need for an adaptive controller that is not based on a mathematical model.

The objective of this thesis was to design and evaluate a position and velocity controller for application to a pneumatic gantry robot. An Adaptive Neural Network (ANN) structure was implemented as both a controller and as a compensator. The implemented ANN had online training as this was considered to be the algorithm that had the greatest potential to enhance the performance of the pneumatic system.

One axis of the robot was used to obtain results for the cases of velocity and position control. Seven different velocity controllers were tested and their performance compared. For position control, only two controllers were examined: conventional PID and PID with an ANN Compensator (ANNC). The position controllers were tuned for step changes in the setpoint. Their performance was evaluated as applied to sinusoid tracking.

It was shown that the addition of ANN as a compensator could improve the performance of both position and velocity control. For position control, the ANNC improved the tracking performance by over 20%. Although performance was better than with conventional PID control, it was concluded that the level of improvement with ANNC did not warrant the extra effort in tuning and implementation.
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## List of Nomenclature

- $a_{ii}$: Elements of matrix $A$
- $A$: Sample matrix
- $A_c$: Cross section of the $x$-axis cylinder
- $b_i^2$, $b_i^3$: Bias of node $i$ in the hidden and output layer, respectively
- $bias$: Activation function bias
- $b_L$: Number of nodes in layer $L$ (for non-Simulink®)
- $C_v$: Coefficient of velocity
- $e_v$, $e_x$: Error in velocity and $x$-axis position, respectively
- $F$: Learning rate of $W$
- $F_a$: Available force
- $G$: Learning rate of $V$
- $h$: Sampling time
- $K_{Ap}$: Differential pressure gain
- $K_p$, $K_i$, $K_d$: Proportional, integral and derivative gains
- $K_v$, $K_z$: Tunable gains in Neural Network block
- $L$: Layer in NN, where input $L=1$, hidden $L=2$, output $L=3$ for a 3-layered NN
- $n_h$, $n_i$, $n_o$: Number of nodes in hidden, input and output layers (for Simulink®)
- $net_i^L$: Sum of the inputs to node $i$ in layer $L$
- $N$: Number of samples
- $p_j$: Input $j$ to the hidden layer from the input layer
- $P$: NN input vector
- $P_a$, $P_b$: Absolute pressure of the side “a” and “b” of the cylinder, respectively
- $r$: Sensor reading
- $S$: Slope of sigmoid activation function
- $u$: Control signal
- $u_{NN}$: NN output
- $v$, $v_x$: $x$-axis velocity and velocity setpoint, respectively
- $V$, $W$: Weight vector for the hidden layer and output layer, respectively
- $V_{Lim}$, $W_{Lim}$: Limits of $V$ and $W$, respectively
- $V_{i,j}^2$: Weight connecting node $i$ in the hidden layer and input $p_j$
- $W_{i,j}^3$: Weight connecting node $i$ in the output layer and node $j$ in the hidden layer
- $x$, $x_s$: $x$-axis position and position setpoint, respectively
- $Z$: Tunable parameter in Neural Network
Acronyms
ANN    Adaptive Neural Network
ANNC   Adaptive Neural Network Compensator
BPA    Back Propagation Algorithm
DOF    Degrees Of Freedom
DZC    Deadzone Compensation
FF     Feed Forward
FL     Fuzzy Logic
GUI    Graphical User Interface
I/O    Input/output
MBPM   Modified Back Propagation Method
MNN    Multilayer Neural Network
NN     Neural Network
P-only Proportional Only
PFC    Proportional Flow Control
PI     Proportional Integral
PID    Proportional Integral Derivative
PPC    Proportional Pressure Control
PWM    Pulse Width Modulation
RMS    Root Mean Square
RMSE   Root Mean Square Error
SMC    Sliding Mode Control
Z/N    Ziegler-Nichols

Greek Letters
ΔRMSE_i Change in the RMSE for case i
ΔP_x   x-axis differential pressure
λ      Adaptation parameter
σ_i    Activation function for node i
Chapter 1

Introduction

Control systems exist in a virtually infinite variety, both in type of application and level of sophistication. Control Engineering can be summed up as the design and implementation of automatic control systems to achieve specified objectives under given constraints. For a complex system, the overall objectives and constraints will need to be translated into performance specifications for the various subsystems – ultimately into control systems specifications for low-level subsystems. Control engineering practice includes the use of better and more efficient control design strategies for improving manufacturing processes, the efficiency of energy use, advanced automobiles, among others. The present challenge to control engineers is the modeling and control of modern, complex, interrelated systems such as navigation control systems, chemical processes and robotic systems.

1.1 Problem Overview

PID is the acronym for the classical and most heavily used control algorithm. Proportional plus Integral plus Derivative (PID) control is sufficient for many control problems, particularly when there are benign process dynamics and modest performance requirements. However, there are numerous control situations in which PID control with constant gains fails to meet the requirements. For example, systems with large parameter variations are candidates for more sophisticated control structures.

Considerable research has been conducted on the control of pneumatic systems due to their potential as a low-cost, clean, high power-to-weight ratio actuators. However, nonlinearities such as those due to compressibility of air continue to limit their accuracy. Among the nonlinearities in a pneumatic system, friction can have a significant effect on tracking performance, especially in applications that use rodless cylinders which have higher Coulomb friction than rodded cylinders.

Compensation for nonlinearities in pneumatic systems has been a popular area of research in pneumatic system control. Most of the compensation strategies use model based algorithms. Although they show relatively good results, the requirement for model parameter identification has made these methods difficult to implement.

A pneumatic gantry robot is an example of a pneumatic system that typically requires a controller more sophisticated than PID. Most advanced nonlinear control strategies are based on...
a detailed mathematical model of the system. If a simplified mathematical model is used, then performance is sensitive to uncertainties and parameter variations. This highlights the need for an adaptive controller that is not based on a mathematical model.

1.2 Objectives

Abu-Mallouh and Surgenor (2008) conducted research on force/velocity control of a pneumatic gantry robot for contour tracking with NN compensation. They used two Proportional Pressure Control (PPC) valves. Both simulation and experimental results were presented. However, the NN compensator was only tested by simulation. They concluded that their work demonstrated the value of NN for online compensation of nonlinear elements in a pneumatic system, but experimental verification was required. The underlying purpose of the thesis is to provide that verification.

The objective of this thesis is to design and evaluate a position and velocity controller for application to one axis of the pneumatic gantry robot. An adaptive NN will be tested as both a controller and as a compensator. The implemented NN will be adaptive with online training as this is an algorithm that appears to have the greatest potential to enhance the performance of a pneumatic system. Performance of the NN will be reported quantitatively. Comparison will be made with the performance of a conventional PID controller, in order to provide a benchmark.

1.3 Thesis Outline

The organization of the thesis is as follows:

- Chapter 2 presents a literature review on six subjects: 1) pneumatic system control, 2) pneumatic control with compensation, 3) Neural Network (NN), 4) NN as a controller, 5) NN as a compensator and 6) online versus offline NN.

- Chapter 3 provides background on the apparatus including sensor calibration. Details on the Adaptive Neural Network (ANN) algorithm will also be given including the implementation and tuning.

- In Chapter 4 the apparatus is used to obtain results for the case of velocity control, in order to evaluate the performance of ANN as applied to one axis of the gantry robot. Seven different controllers are tested and their performance compared: 1) P-only, 2) PI, 3) PI+ΔP, 4) ANN, 5) ANN+ΔP, 6) P-only+ANNC (ANN compensator) and 7) PI+ANNC. For ANN and ANN+ΔP, ANN is applied as a stand-alone controller. For P-only+ANNC and PI+ANNC, ANN is applied as a compensator.
In Chapter 5 the apparatus is used to obtain results for the case of position control, in order to evaluate the performance of ANN as a compensator. It provides the tuning methodology and comparative performance results. Two controllers are tested: 1) PID and 2) PID+ANNC. The controllers are tuned for step changes in the setpoint. Their performance is evaluated as applied to sinusoid tracking.
Chapter 2

Literature Review

This chapter presents a literature review on six subjects: 1) pneumatic system control, 2) pneumatic control with compensation, 3) Neural Network (NN), 4) NN as a controller, 5) NN as a compensator and 6) online versus offline NN.

2.1 Pneumatic System Control

Pneumatic actuators are difficult to control because of low bandwidth and high nonlinearity due mainly to air compressibility and Coulomb friction effects. However, relative to electrically actuated systems, pneumatic systems are cheaper and easier to maintain. This observation has led to considerable interest and research on pneumatic system control. Two specific examples will be given in this section. They were chosen as they gave quantitative and comparative performance results for different control schemes.

van Varseveld and Bone (1997) implemented a fast, accurate, and inexpensive position-controlled pneumatic actuator. Figure 2-1 illustrates the pneumatic system that they used. The system used a standard rodded pneumatic cylinder (stroke = 152 mm, diameter = 27 mm) with two on/off solenoid valves. The valves were pulsed using a novel Pulse Width Modulation (PWM) algorithm which produced a very linear open-loop velocity response. Four different schemes of PWM were examined.

![Figure 2-1 Schematic of pneumatic control system with solenoid valves (van Varseveld and Bone, 1997)](image-url)
Figure 2-2 shows the closed-loop position controller step response for the different PWM schemes. The results led them to use PWM Scheme 4 due to its better transient response. Then, they added basic friction compensation to the PID controller with PWM Scheme 4. Figure 2-3 illustrates the results for the PID position controller with and without friction compensation. They reported that adding a friction compensator could reduce the average of steady-state error by 40%, from 0.19 mm without the compensator to 0.11 mm with the compensator.
Chillari et al (2001) conducted several experiments on pneumatic system control. They examined PID, Fuzzy, Sliding mode and Neuro-Fuzzy controllers. Experimental results for these controllers applied to different setpoint trajectories were presented. Main parts of the apparatus were: rodded pneumatic cylinder (stroke = 200 mm, diameter = 25 mm) and two pairs of on/off solenoid valves.

The controllers were tested on sinusoidal, square, saw-tooth and staircase input signals. In their work, Chillari et al adopted a differential pressure ($\Delta P$) feedback signal in order to compensate for external disturbances and also friction forces that would act against the motion. Figure 2-4 shows the Fuzzy control with $\Delta P$ feedback for a sine wave. Unfortunately, they did not present a figure which shows the controller without the $\Delta P$ feedback. In addition, they introduced a NN which was able to estimate the $\Delta P$ feedback and could be used instead of the differential pressure sensor.

Figure 2-4 Fuzzy control with $\Delta P$ feedback for sine wave input (Chillari et al, 2001)

Figure 2-5 presents a quantitative performance comparison of the different controllers based on the standard deviation between the desired and the actual position signal in $m$. According to Figure 2-5, the error increases as the frequency of the signal increases. The Fuzzy controller showed slightly better performance than the PID controller. Adoption of the $\Delta P$ feedback improved the performance of the Fuzzy controller still further. The performance of the Fuzzy controller with the NN estimate of $\Delta P$ was comparable to that of the Fuzzy controller with real $\Delta P$ feedback.
2.1.1 Pneumatic Control with Compensation

As discussed in the previous section, van Varseveld and Bone (1997) used a basic Coulomb friction compensation combined with bounded integral control which was found to substantially reduce the steady-state error due to stiction. At zero velocity, the friction force known as stiction is largely responsible for any steady-state error. Friction compensation was disabled once the steady-state error was within a specified tolerance. The results of applying the controllers on step input and S-curve were shown in Figure 2-2 and Figure 2-3, respectively.

One of the common compensators in pneumatic controls is deadzone (dead time) compensation. The deadzone is an inherent nonlinearity in pneumatic servo valves, where for a range of input control values, the valve gives no output flow. From Ning and Bone (2002), Figure 2-6 illustrates the measured relationship between the maximum cylinder force versus the valve input (Part a) and the schematic of a servo pneumatic valve showing chambers A and B (Part b). There are three situations for the spool of valve based on the valve input. First, if the valve input is greater than $x_{af}$, chamber A is filling. Second, if the valve input is less than $x_{bf}$, chamber B is filling. Third, if the valve input is in between $x_{af}$ and $x_{bf}$, the applied force is less than the static friction force. In the third case, the cylinder does not move and this is called the deadzone.

![Figure 2-5 Performance comparison for different controllers and setpoints (Chillari et al, 2001)](image)
(a) Measured relationship between the maximum cylinder force and the valve input

(b) Schematic of a servo pneumatic valve showing chambers A and B

Figure 2-6 Working principle of a servo pneumatic valve (Ning and Bone, 2002)

Figure 2-7 gives the block diagram of the control system with friction compensation used in their paper. A Proportional plus Velocity plus Acceleration (PVA) position controller was adopted. A friction compensation block was added as a feedforward signal to the PVA output. Unfortunately, the authors did not provide any mechanical specifications for the apparatus. They did mention that a rodless cylinder was used.

Figure 2-7 Block diagram of the PVA controller with friction compensation (Ning and Bone, 2002)
In Ning and Bone (2002), when the cylinder was in the deadzone, a friction compensation term was added to the control signal to make the cylinder move until it reached the desired steady-state error value. The friction compensation parameters had to be tuned by the user. However, no tuning procedure was presented. They deployed both PV and PVA controllers. Since they used double differentiation for the acceleration feedback, significant noise was seen in the signal. The controller was set to PVA initially. It would be switched back to PV when the piston was 5 mm away from the setpoint. Figure 2-8 illustrates the experimental position and error responses of PVA/PV control where they could get a steady-state accuracy of ±0.01 mm. The proportional, velocity and acceleration gains are given. No comparison of performance was presented between the controller with and without the friction compensation.

![Figure 2-8 Experimental position and error signals of PVA/PV position control (Ning and Bone, 2002)](image)

Ning and Bone (2005) conducted an experimental comparison of two servo pneumatic position control algorithms: PVA + feedforward (FF) + deadzone compensation (DZC) and Sliding Mode Control (SMC). They used a rodless cylinder with a Proportional Flow Control (PFC) valve. The DZC was the same as the one used in Ning and Bone (2002). Figure 2-9 gives the block diagram of the PVA+FF+DZC controller.

The tracking performances were evaluated by the RMSE. The PVA+FF+DZC controller had a RMSE of 0.910 mm for a sinusoid at 0.5 Hz. For the same sinusoid tracking, SMC could reduce the RMSE to 0.375 mm.
Andrighetto and Bavaresco (2009) reported success in using deadzone compensation for their pneumatic apparatus. They used a pneumatic rodless cylinder (stroke = 500 \text{ mm}, diameter = 25 \text{ mm}) and a 5 port 3 way PFC valve (the same valve used in this thesis). Figure 2-10 shows the experimental result for a sinusoidal input where deadzone compensation is added to a tuned P-only position controller. Specifically, the input was a sinusoidal wave at 1.6 \text{ Hz} and amplitude of 200 \text{ mm}. The maximum error was around 70 \text{ mm} without deadzone compensation which was reduced to 20 \text{ mm} with the compensation (70\% reduction in the error). They claimed that the deadzone compensation was fairly easy to implement. Despite this statement, they mentioned that this method is only applicable when the deadzone is known and the valve dynamics are fast enough to be neglected.
Figure 2-10 P-only position controller with and without deadzone compensation (Andrighetto and Bavaresco, 2009)
Kosaki and Sano (2009) studied an observer-based friction compensator for position control of a pneumatic system. The observer was used to estimate the dynamically varying friction force online. Basically, they modified the friction observer proposed by Friedland and Park (1992) for pneumatic control. They added a term to consider the pressure effects inside the actuator chambers. A rodded pneumatic cylinder was used (stroke = 400 mm, diameter = 50 mm). The control loop consisted of inner pressure proportional derivative (PD) and outer position PD controllers with a friction observer. Figure 2-11 gives the estimation of friction force using the observer which shows 68.5% improvement in reference to that of Friedland and Park (1992).

![Figure 2-11 Estimation of friction force using the proposed observer (Kosaki and Sano, 2009)](image)

In Figure 2-12, one is able to see the PD position controller with friction observer result. The friction observer could reduce the steady-state value from 4 mm (with all gains tuned) and 10 mm (with all gains fixed) to 0.075 mm. This represents a 98% reduction in the error relative to the case with all gains tuned. Finally, they mentioned that using their friction observer requires one to identify the system parameters for different operating conditions in terms of the apparatus dynamics. Thus, this technique is considered to be a model based friction compensator.

![Figure 2-12 PD position controller with friction observer result (Kosaki and Sano, 2009)](image)
Mao et al (2009) examined a control strategy for a rotary pneumatic position system based on a feedforward compensation pole-placement self-tuning method. Only simulation results were presented. Figure 2-13 illustrates the apparatus in which they used a PFC valve and a pneumatic rotary cylinder. They did not present any mechanical specifications of the system.

For the mathematical model, they assumed: 1) the air is considered to be an ideal gas 2) the process is isoentropic adiabatic 3) the temperature variation in the rotary cylinder chambers is ignored and 4) the cylinder leakage is ignored.

Figure 2-14 gives the block diagram of the pole-placement self-tuning controller. The essence of the pole-placement method is to determine the feedback control law which can put the poles of the closed-loop transfer function in specified locations.
Figure 2-15 and Figure 2-16 give the controller result with a square wave input without and with a 10 kg payload, respectively. They reported less than 1º steady-state error for the system. This equates to a modest 3.3% error on a 30º step size. The control parameters are seen to converge to steady-state values after less than three cycles or 5 s. However, they did not compare their results with a different controller to show the significance of using the pole placement strategy. The pole-placement method requires system parameter identification which makes it a model based controller.

![Figure 2-15 Pole-placement self-tuning controller result (Mao et al, 2009)](image1)

![Figure 2-16 Pole-placement self-tuning controller result with 10 kg payload (Mao et al, 2009)](image2)
2.2 Neural Network

The modeling of Neural Networks (NNs) is based on biological processes for information processing, specifically the nervous system. The basic unit of NNs is the neuron. A neuron receives signals from other neurons through its dendrites. The signals are added in the cell body after they multiplied by a coefficient (i.e. weight). When this summation reaches a threshold value, the neuron “fires” and a signal known as the action potential is sent through the axon to the synapses. Synapses are the junctions through which neurons send signal to each other. Each neuron connects to about 1000 others. The signal conveyed between neurons is an electric potential in nature. When a neuron sends a signal it is exactly the same signal to all the neurons it is connected to. A NN is a mathematical model with adjustable parameters that sets out to mimic this biological structure. A NN is trained from a set of input-output examples. These examples represent what the network should output when it is shown a particular input (Norgaard et al, 2002). Further details regarding NN background can be found in the Doctoral thesis of Abu-Mallouh (2008).

Figure 2-17 shows the structure of a typical multi layered NN. There can be one or more hidden layers between Input and output nodes. If information goes from the input layer to the output layer, it is called a feedforward NN (i.e. there are no recurrent or backward connections). In an NN, the activation function of a node defines the output of that node given an input or set of inputs. One of the most common activation functions is the sigmoid function as given by:

$$\sigma_i(net_i) = \frac{1}{1 + e^{-net_i}} \tag{2-1}$$

![Figure 2-17 Multi layer NN (Demuth et al, 2006)](image)
As discussed in the previous sections, pneumatic systems are highly nonlinear because of air compressibility and friction forces. Nonlinearity in control with pneumatic actuators can be considered in two ways: one is with a detailed model based controller as in Richer and Hurmuzlu (2000) and the other is non model based controller as in Kaitwanidvilai and Parnichkun (2005). Even though the experimental results for the model based controllers are better than the results for the non model based controllers, the latter avoids problems due to model uncertainties. Thus, control of nonlinear systems is a major application area for NN. In the following subsections, the applications of a NN as a controller and as a compensator will be reviewed.

2.2.1 NN as a Controller

A NN can be implemented as a controller in as system in two ways: 1) direct control and 2) indirect control. In direct NN control, the NN is the controller. This type usually needs online training. These are some the examples of direct NN: direct inverse model control, feedforward with NN inverse model control and NN internal model control as shown in Figure 2-18 and Figure 2-19, respectively (Abu-Mallouh, 2008).

Indirect NN control means that a non NN controller uses a NN model of the system for tuning or compensation. In this case the mail controller is not a NN. In this type, the NN is used to model the system to be controlled in order to assist the main controller. The NN in this case is usually trained offline. Figure 2-20 shows an indirect example of NN control (Abu-Mallouh, 2008).

Considerable research has been conducted in using NNs for system identification and indirect control of nonlinear systems, while less work has been done on using NNs in direct controllers (Huang and Lewis, 2003). NN as an indirect controller in a system is known as compensator. Further background on NN as a compensator will be presented in the next section.
Little research has been done on investigating the performance of NNs as controllers. Most of the applications of NNs involve indirect controllers, where the NN is used as a model predictor or as a compensator. One exception is Burton et al (1999) who tested three different controllers for a hydraulic actuator system: 1) simple open loop profile follower, 2) PID neural controller (NN as compensator) and 3) NN controller. Figure 2-21 illustrates the block diagram of their NN controller. The control parameters were force and position. They used a mathematical model as a reference model in parallel with the actual model in order to reduce coupling effects. Figure 2-21 shows that they also added a network learning algorithm to provide updates to the NN controller weights. No further details were provided regarding the algorithm.
The NN was trained offline. Figure 2-22 provides simulation results for the PID position and force controller. The setpoint was a 1 Hz sinusoidal signal for both position (-50±250 mm amplitude) and force (1750±1500 N amplitude). Figure 2-23 gives the NN controller result for the same 1 Hz sinusoidal signal on position (±300 mm amplitude) and force (1750±1250 N amplitude). No quantitative performance measures were provided. However, by comparing Figure 2-22 and Figure 2-23, NN controller shows better performance in terms of setpoint tracking and reduced oscillations. Burton et al noted that the NN tended to fail in the deadzone region. Thus, they augmented the NN with a “kicker” which was essentially a pulse signal. They only used the kicker when the system was close to the deadzone.
Figure 2-22 Simulation results for PID position and force controller, 1 Hz sinusoidal input (Burton et al, 1999)

Figure 2-23 Simulation results for NN position and force controller, 1 Hz sinusoidal input (Burton et al, 1999)
2.2.2 NN as a Compensator

In Section 2.1.1, different model based compensators in pneumatic control were examined. The difficulty of system parameter identification has been the motivation to conduct research on non model based compensators. Success has been reported with the use of NNs for the compensation of system nonlinearity, including lag in Huang and Lewis (2003) for a simulated electric robot manipulator system.

Lewis et al (1996) developed an indirect multilayer nonlinear NN-based controller for a serial link electric robot. The algorithm was originally termed as the Modified Back Propagation Method (MBPM). In MBPM, an improved weight tuning method is used to correct for deficiencies that result when NN with standard BPA is used in the presence of unmodeled disturbances. The improved tuning algorithm makes the NN strictly state passive (i.e. bounded weights are guaranteed). Also, they provided the Lyapunov stability analysis for the system and they proved that they system is stable in the sense of Lyapunov.

The strategy in Lewis et al’s work was to use the NN as a feedforward compensator to negate the nonlinearities and enable a conventional controller to deal with the linearized system. Its success depends on a property of NN in which for every smooth function \( f(x) \), there exists a NN with \( \sigma \) as the activation function such that:

\[
f(x) = W^T \sigma(V^T x) + \varepsilon
\]  

for weights \( W, V \). They also noted that, in the presence of unmodeled disturbances, the tracking error does not vanish but it is bounded. Furthermore, relatively small tracking errors can be achieved with relatively high NN gains. They pointed out that slow learning rates can cause the NN to oscillate over the global minimum (Lewis et al, 1998).

It is worth mentioning that the advantage of NN relative to conventional adaptive control is that there is no need to have the preconditions of having a known regression matrix and linearity in the unknown system parameters as there is in adaptive control (Lewis et al, 1998).

The proposed MBPM is trained online. The weights can be easily initialized and trained. Thus, no offline training is required. Figure 2-24 illustrates the three layered NN that they used where \( y \) is one of the out layer elements. The NN controller inputs are \( P = [e^Te^T q_s^T \dot{q}_s^T \dot{q}_s^T]^T \) where \( q \) is the joint variable and \( e \) represents the tracking error. The subscript \( s \) denotes the setpoint. They did not explain their selection of inputs to the NN.
Figure 2-25 illustrates the block diagram of their MBPN compensator. They used a proportional plus derivative (PD) controller with a NN feedforward. Thus, they did not provide any tuning procedure for the PD term. The control structure includes $q \equiv [q^T \dot{q}^T]^T$ and $e \equiv [e^T \dot{e}^T]^T$.

Figure 2-26 gives MBPN angular position compensator results with representative weight estimates. Since there were no quantitative performance measures given in the paper, it is difficult to judge whether this represents good tracking performance. The responses are given for both of the joint variables. According to Figure 2-26, NN weights keep changing while the input is changing.
Figure 2-25 Block diagram of the MBPN as a compensator (Lewis et al, 1996)

Figure 2-26 Results for MBPN compensator with representative weight estimates (Lewis et al, 1996)
As far as NN tuning is concerned, Lewis et al (1998) mentioned that if the NN parameters are set at one operating condition and tested on another, the NN may not be able to converge when training. Figure 2-27 shows a representative one layer NN error surface plot. If the weights are initialized as in case 1 (bad IC), there is a possibility that the NN might find the local minimum and not the global minimum. However, using a better technique such as learning with momentum (case 2) can make the system ignore the local and continue on to the global minimum. Case 3 shows that if the learning rate is too large, the system fails to converge.

In pneumatic control, Choi et al (1998) studied feedback linearization by means of a NN for position control. Figure 2-28 illustrates the apparatus used for the experiments. It consisted of a double-acting rodless cylinder (stroke = 200 mm, diameter = 25 mm) and a five port three way PFC valve. The controller had an inner PID pressure controller and an outer PID position controller with indirect NN for feedback linearization. Figure 2-29 gives the block diagram of the controller.

The NN was trained offline with BPA. Figure 2-30 shows the PID controller result with and without NN feedback linearization for a sinusoidal wave at 0.2 Hz. They could achieve an average error of 0.8 mm with PID+NN which represents a 74% improvement over the PID controller.
Figure 2-28 Schematic of pneumatic control system with a PFC valve (Choi et al, 1998)

Figure 2-29 Block diagram of the PID position controller with NN feedback linearization (Choi et al, 1998)
Figure 2-30 PID controller result with and without NN feedback linearization, sinusoidal wave at 0.2 Hz (Choi et al, 1998)
Gross and Rattan (1997) conducted a research on using NN as a compensator for velocity control of a pneumatic actuator. Only simulation results were presented. They used two controllers: 1) PID with position feedback and 2) PI with acceleration feedback. Figure 2-31 provides simulation results of the controllers for a desired trajectory at the speed of 560 mm/s (22 in/s). It shows that PI with acceleration has a better performance. They reported that the Root Mean Square Error (RMSE) of the PI with acceleration feedback was 48 mm/s while the RMSE of the PID with position feedback was 100 mm/s.

They used a Multilayer NN (MNN) to improve the tracking performance. MNN was applied as an open-loop controller, as a feedforward to PID with position feedback and PI with acceleration feedback. The block diagrams of the position controllers tested are shown in Figure 2-32 and Figure 2-33. According to the figures, the position setpoint and its derivative were the only inputs to the MNN block. The position setpoint was derived from the desired velocity profile. They did not provide any reason why they selected these inputs. The MNN was trained offline using BPA with three different velocity profiles. They used MNN in a feedforward loop to provide inverse dynamics to cancel the nonlinear effects. It should be noted that model based inverse dynamics is considered to be difficult to implement because it needs an exact model of the system (Spong and Vidyasagar, 1989).
Figure 2-33 Block diagram of position feedback PID controller with MNN compensator
(Gross and Rattan, 1997)

Figure 2-34 provides a comparison of the three tested controllers: 1) MNN open-loop, 2) PID+MNN with position feedback and 3) PI+MNN with acceleration feedback. PI+MNN with acceleration feedback shows the best performance with the RMSE value of 1 mm/s which is 98% better than that of the conventional PI velocity controller without MNN feedforward. PID+MNN is the second best by RMSE value of 19 mm/s which is 81% better than that of the conventional PID velocity controller without MNN feedforward. However, MNN open-loop shows a disappointing performance with RMSE value of 205 mm/s. They did not provide any reason for such a bad result but they acknowledged that the trajectory tracking performance could be enhanced by using an adaptive MNN.

Figure 2-34 PI and PID result with MNN compensator (Gross and Rattan, 1997)
Li and Asakura (2003) conducted research on using NN as a compensator for the control of a 2-link pneumatic manipulator. Simulation and experimental results were presented. A PD angular position controller with a NN compensator was adopted. Figure 2-35 shows the block diagram of the PD position controller with the NN compensator. $\theta, \theta_s,$ and $\theta_e$ are joint angle, position setpoint and angular position error, respectively. The NN signal is added to the controller signal. There were two different transfer functions for different air tube lengths: one transfer function for a tube length of 2 to 20 $m$ and a second transfer function for a tube length above 20 $m$.

![Figure 2-35 Block diagram of the PD angular position controller with the NN compensator (Li and Asakura, 2003)](image)

A three layered NN was trained online with BPA. Figure 2-36 gives the simulation result comparison of the PD angular position controller with and without NN compensator for an air tube length of 60 $m$. The results are for two step inputs for the two joint angles. According to the figure, PD with NN compensator shows better performance. PID+NN has faster settling time, less steady-state error and far less degree of oscillation relative to PD. They reported the performance of PD with NN compensator as follows: $RMSE$ of $\theta_1$ is 0.34$^\circ$ (0.26% on a 130$^\circ$ step) and for $\theta_2$ is 0.12$^\circ$ (0.24% on a 50$^\circ$ step).

Figure 2-37 illustrates the experimental results for the PD with NN controller for an air tube length of 60 $m$. According to the figure, PD with NN compensator again shows a better performance. They reported the performance of PD with NN compensator as follows: $RMSE$ of $\theta_1$ is 0.35$^\circ$ (0.27% on a 130$^\circ$ step) and for $\theta_2$ is 0.21$^\circ$ (0.42% on a 50$^\circ$ step).
By comparing the simulation and experimental results, one observes that for $\theta_1$, the PD response for the experimental results has higher error (maximum 230° for simulation, maximum 250° for experimental). For $\theta_2$, that maximum angular position is higher for experimental results than that for the simulation results (maximum 70° for simulation, maximum 110° for experimental). In terms of PD+NN controller, the response for $\theta_1$ is comparable in both simulation and experimental results. However, the settling time for simulation is about 6 s and that of experimentation is about 7 s. On the other hand, for $\theta_2$, the settling time for experimentation is less than simulation (5 s for simulation, 3 s for experimentation). The maximum overshoot in the simulation is 70° and that of experimentation is 110°.

Li and Asakura investigated the air tube lengths which resulted in time delays that ranged from 0.012 to 0.12 s. Although, they reported success in using the NN compensator, the time for the system to reach equilibrium was relatively long (4.5 s for Figure 2-36 and 6.5 s for Figure 2-37). They did not provide any reason why they selected $\theta, \theta_2, \theta_c$ as the NN block inputs.
Figure 2-36 Simulation results comparison of the PD controller with and without NN compensator for an air tube length of 60 m (Li and Asakura, 2003)

Figure 2-37 Experimental results comparison of the PD controller with and without NN compensator for an air tube length of 60 m (Li and Asakura, 2003)
Wang and Peng (2003) used an online NN as both a controller and a “model predictor” (compensator) for position control of a pneumatic actuator with Proportional Pressure Control (PPC) valves. The pneumatic system was a two DOF robotic manipulator. Each joint was controller separately but with the same controller structure. Figure 2-38 gives the block diagram of the NN angular position controller with NN compensator.

The idea of having NN as both the controller and the compensator is considered unique. However, they did not provide any information regarding the nature of the tests. There was no information presented on how they selected the NN inputs. They did not compare results with other controllers. Finally, they did not provide results with and without NN compensator to provide a measure of whether their proposed novel controller was better than a conventional controller.

Kothapalli and Hassan (2008) used a NN to adjust the gains of a PI position controller for a pneumatic system. Figure 2-39 illustrates the block diagram of the PI position controller with NN based gain estimator. The pneumatic system consisted of a PFC valve and a rodless cylinder (stroke = 500 mm, diameter = 15 mm). They also investigated the effect of external forces on the controller.

The NN was trained offline with momentum BPA. The addition of “momentum” to BPA makes the NN avoid getting stuck in local minimum. In addition, when all weight changes are all in the
same direction, the momentum amplifies the learning rate causing a faster convergence (Demuth et al., 2006). According to Figure 2-39, they selected $x$ and $x_i$ as the inputs to the NN. However, they did not explain why they chose these inputs.

![Figure 2-39 Block diagram of the PI position controller with NN based gain estimator (Kothapalli and Hassan, 2008)](image)

Figure 2-40 gives the PI position controller simulation results under a variable external force. Figure 2-41 gives the PI position controller with NN gain estimator simulation results under a variable external force. Since no quantitative performance measures were provided, one has to compare Figure 2-40 and Figure 2-41 directly. In terms of steady-state error, for the period 1 to 4 $s$, PI+NN has lower steady-state error relative to PI controller. PI+NN has an acceptable degree of oscillation. Finally, the PI+NN controller is seen to have a settling time of about 1 $s$ while the PI controller has a settling time of about 4 $s$. However, the initial error of the PI+NN (~ 150 $mm$) is higher than that for PI (~ 60 $mm$) and the error is worse than PI in the period 4 to 5 $s$. Overall, the addition of NN is considered to improve the performance.
Figure 2-40 PI position controller results under a variable external force (Kothapalli and Hassan, 2008)

Figure 2-41 PI position controller with NN gain estimator results under a variable external force (Kothapalli and Hassan, 2008)
Abu-Mallouh and Surgenor (2008) conducted research on force/velocity control of a pneumatic gantry robot for contour tracking with NN compensation. They used two PPC valves. Both simulation and experimental results were presented. However, the NN compensator was only tested by simulation. Figure 2-42 shows the block diagram of the PI+NN controller.

![Figure 2-42 Block diagram of PI+NN controller (Abu-Mallouh and Surgenor, 2008)](image)

The NN structure that they used was the same as the one used in this thesis, which is Adaptive Neural Network (ANN) (please refer to Chapter 3). Figure 2-45 gives the simulation results for PI and PI+NN controllers. The addition of NN reduced the force $RMSE$ from 2.68 N for the PI controller to 0.83 N for the PI+NN (70% improvement). It also reduced the velocity $RMSE$ from 0.042 m/s for the PI controller to 0.025 m/s for the PI+NN (30% improvement). They concluded that their work demonstrated the value of NN for online compensation of nonlinear elements in a pneumatic system, but experimental verification was required.

Several papers on the application of NN as a compensator were presented in this section. Some researchers added the NN compensation to the overall control signal: Gross and Rattan (1997), Li and Asakura (2003) and Abu-Mallouh and Surgenor (2008). However, some researchers subtracted the NN compensation from the overall control signal: Lewis et al (1996) which proposed the basis of the ANN method, Gi et al (1998) and Wang and Peng (2003). They state that by subtracting the output of the NN compensator, the nonlinear terms would be negated.
2.2.3 Online versus Offline NN

Little research has been conducted on the comparison of online and offline training for applications of NN in the field of control systems. There appears to be none reported in the field of pneumatics, but there is some in other fields. For example, Puttige and Anavatti (2007) tested online and offline training NN models for an Unmanned Aerial Vehicle (UAV). Simulation results based on the system models were presented. The results were validated by experiment.

Figure 2-44 gives the block diagram of the offline NN model showing 10 inputs. They used the inputs to train the NN offline. Then, they added the trained NN model to the system as a model predictor. For the online training case, they used the same NN structure and applied it to the control system was running. Figure 2-45 gives a comparison of the actual system model, offline NN model and online NN model. The results are presented for roll, pitch and yaw (i.e. three degree of rotations of the UAV). Inspection of the figure shows little difference between the models, especially between online and offline NN models. Unfortunately, they did not discuss the significance of using offline NN versus online NN training. They did mention that online NN takes more time to converge. However, they did not comment on whether online NN negatively or positively affected system performance.
Figure 2-44 Block diagram of the offline NN model (Puttige and Anavatti, 2007)

![Block diagram of the offline NN model](image)

Figure 2-45 Comparison of the model outputs, offline vs. online NN models (Puttige and Anavatti, 2007)

![Comparison of model outputs](image)
Fan et al (2004) studied the difference between online and offline training strategies for a NN. They presented an online video-based face recognition system using modified probabilistic NN. They pointed out that their methodology for online and offline training was the same. They did not compare the results. Their opinion was that the online training has some advantages over offline training. For instance, their online system could add faces continuously to its database and improve the accuracy as the database increased in size. An offline NN cannot update the database with new faces. Thus, they are not as flexible as online NNs.

2.3 Summary
This chapter presented a literature review on six subjects: 1) pneumatic system control, 2) pneumatic control with compensation, 3) Neural Network (NN), 4) NN as a controller, 5) NN as a compensator and 6) online versus offline NN. The following can be presented as the main observations:

- Considerable research has been conducted on the control of pneumatic systems due to their potential as a low-cost, clean, high power-to-weight ratio actuators. However, nonlinearities such as those due to compressibility of air continue to limit their accuracy.

- Among the nonlinearities in a pneumatic system, friction can have a significant effect on tracking performance, especially in applications that use rodless cylinders which have higher Coulomb friction than rodded cylinders.

- Compensation for nonlinearities in pneumatic systems has been a popular area of research in pneumatic system control.

- Most of the compensation strategies use model based algorithms. Although they show relatively good results, the requirement for model parameter identification has made these methods difficult to implement.

- Using NN as a non model based algorithm is a potential solution for nonlinear term compensation in pneumatic systems.

- Most of the research on pneumatic system control with compensation has been conducted for position control. Less research has been conducted for velocity control.

- The most common performance measure for step inputs is the steady-state error.

- The most common performance measures for sinusoidal inputs are Root Mean Square Error (RMSE) and Average Error (AVGE).
Little research has been done investigating the use of NNs as direct controllers. Most of the applications of NNs are as indirect controllers or compensators.

In the context of NN as a compensator, some researchers added the NN signal to the overall control signal and some subtracted the NN signal from the overall control signal.

Little research has been conducted on online versus offline NN training.

The key observation from the literature review is that a NN appears to have the potential to improve the performance of a pneumatic system, as a compensator for system nonlinearities, with training conducted online to provide an adaptive feature. Previous work has been mainly simulation in nature, and there is little experimental evidence or quantitative comparison of performance with conventional control schemes. This then confirms an opportunity for this thesis to investigate the potential of an adaptive NN experimentally.
Chapter 3

Apparatus and ANN Implementation

This chapter provides background on the apparatus including sensor calibration. Details on the Adaptive Neural Network (ANN) will also be given including the implementation in Simulink®.

3.1 Apparatus Description

The original mechanical design of the pneumatic gantry robot was done by Raoufi (2003) for his Masters thesis. Some changes were made to the apparatus by Abu Mallouh (2008) for his Doctoral thesis. In particular, the original manual flow control valves were replaced with Proportional Pressure Control (PPC) valves. For the purposes of this thesis, the PPC valves were replaced with Proportional Flow Control (PFC) valves. This change was made due to one of Abu Mallouh’s main recommendations, namely to replace the PPC valves with PFC valves in order to improve the response time of the control valves. The data acquisition system was also rewired in order to reduce the level of sensor signal noise seen in Abu Mallouh’s results.

Figure 3-1 illustrates the gantry configuration of the pneumatic system, with three DOF, labeled as the x-axis, y-axis and z-axis. The y-axis consists of two rodless pneumatic cylinders. The x-axis is a single rodless pneumatic cylinder (bore 32 mm, stroke 1 m) which also acts as the gantry bridge for the two y-axis cylinders. The mechanical coupling of the two y-axis cylinders with the x-axis cylinder was sufficient to avoid the synchronization problems that sometimes arise with this configuration. The z-axis is a rodded pneumatic cylinder with integral linear guides. As labeled in Figure 3-1, the end effector of the z-axis is a 2-axis force sensor that ends with a bearing for contact with the workpiece. The z-axis is in the same direction as the y-axis, but it is labeled this way in order to highlight the availability of a third DOF (Taghizadeh et al, 2010).

In this thesis the focus is on x-axis control. Thus, the y-axis and z-axis cylinders were not used. The technical specifications of all the system components are given in Appendix A. Information regarding pressure and position sensor calibrations of the z-axis are given in Appendix C. This is provided for future work that will involve extending the research to z-axis control.

Figure 3-2 shows the pneumatic circuit that is used in the system for x-axis cylinder control. In the figure, one is able to see the main parts used in the circuit. The cylinder is seen to be controlled by a 5 port 3 way proportional flow control (PFC) valve. Position and velocity were measured directly with wire linked potentiometers and tachometers, respectively. The wire linkage uses a constant torsion spring and this “wire force” cannot be neglected. Pressure transducers measure the differential air pressure directly across the x-axis cylinder. Data
acquisition system and the controller board were PC-based with a dSPACE®/DSP as the data acquisition hardware/software and MATLAB/Simulink® as the software. Sampling time was 1 msec. The pressure supply was 500 kPa (72.5 psi) as regulated by a manual pressure regulator. The weight of the x-axis carriage is 7.3 kg. The Coulomb friction force for the x-axis is determined to be 35 N (Abu Mallouh, 2008). The available force in N can be calculated as follows:

\[
F_a = \max(\Delta P_x) \times A_c
\]  

(3-1)

where \( \Delta P_x \) is the x-axis differential pressure (maximum value 500 kPa) and \( A_c \) is the cross section of the cylinder. After substituting these parameters, \( F_a \) is calculated as 128 N. Thus, for the x-axis cylinder, the Coulomb friction is 27% of the maximum available force. In motion control, anything more than 10% is considered a high friction application (Abu Mallouh and Surgenor, 2007).

Figure 3-1 Pneumatic system with the carriage highlighted
Figure 3-2 Pneumatic circuit used for x-axis cylinder control
3.1.1 Sensors

A cable extension transducer measured the cylinder position \((x)\) and velocity \((v)\) along the \(x\)-axis. The transducer is a combination position and velocity transducer. A precision plastic-hybrid potentiometer provides accurate position feedback while a self-generating DC tachometer provides a velocity signal that is proportional to the speed of the traveling stainless steel measuring cable. The \(x\)-axis cylinder was connected to a transducer with a range of 1270 \(mm\).

A differential pressure sensor was used to measure the differential pressure \((\Delta P_x)\) between the two chambers of the cylinder along the \(x\)-axis. A silicon differential pressure sensor was used with a bridge sensor signal conditioner. Both have a differential pressure range of 689 \(kPa\) (100 \(psi\)). A signal conditioner was used to amplify the differential pressure sensor voltage output.

3.1.2 Data Acquisition

Data acquisition system and controller board were PC-based with dSPACE/DSP as the data acquisition hardware/software and MATLAB/SIMULINK as the software. The DS1104 R&D controller board is a real-time hardware based on PowerPC technology. There are a total of eight A/D channels (inputs): 4 are multiplexed with a resolution of 16 bits and conversion time of 2 \(msec\) and the other 4 are parallel channels with 12 \(bits\) resolution and 800 \(ns\) conversion time. There are 8 channels of D/A (outputs) with 16 \(bits\) of resolution and a settling time of 10 \(\mu s\). Table 3-1 shows the signal and channel assignments. These technical specifications were taken from Abu-Mallouh (2008) Doctoral thesis.

Table 3-1 gives a summary of the main features of each of the major components used in the apparatus. The technical information and datasheets of the parts are given in Appendix A.

<table>
<thead>
<tr>
<th>Input Channel</th>
<th>Signal</th>
<th>Resolution ((bits))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ch1 (A/D)</td>
<td>(x)-axis position ((x))</td>
<td>16</td>
</tr>
<tr>
<td>Ch4 (A/D)</td>
<td>(x)-axis differential pressure ((\Delta P_x))</td>
<td>16</td>
</tr>
<tr>
<td>Ch5 (A/D)</td>
<td>(x)-axis velocity ((v))</td>
<td>12</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Output Channel</th>
<th>Signal</th>
<th>Resolution ((bits))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ch2 (D/A)</td>
<td>(x)-axis control output ((u))</td>
<td>16</td>
</tr>
</tbody>
</table>
Table 3-2 Summary of main features of major components used in the apparatus (Abu-Malloh, 2008)

<table>
<thead>
<tr>
<th>No.</th>
<th>Component</th>
<th>Model</th>
<th>Axis</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cable extension for position</td>
<td>DV301</td>
<td>x-axis</td>
<td>±0.1% of full stroke = ± 1.3 mm</td>
</tr>
<tr>
<td>2</td>
<td>Cable extension for position</td>
<td>DV301</td>
<td>z-axis</td>
<td>±0.1% of full stroke = ± 0.13 mm</td>
</tr>
<tr>
<td>3</td>
<td>Cable extension for velocity</td>
<td>DV301</td>
<td>x-axis</td>
<td>±3% at the rate 42 mm/s = ± 1 mm/s</td>
</tr>
<tr>
<td>4</td>
<td>Cable extension for velocity</td>
<td>DV301</td>
<td>z-axis</td>
<td>±3% at the rate 42 mm/s = ± 1 mm/s</td>
</tr>
<tr>
<td>5</td>
<td>Proportional flow valve</td>
<td>FESTO MPYE</td>
<td>x &amp; z axes</td>
<td>Not Available</td>
</tr>
<tr>
<td>6</td>
<td>Differential pressure sensor</td>
<td>PX137</td>
<td>x &amp; z axes</td>
<td>±0.1% of full scale = ± 0.7 kPa</td>
</tr>
<tr>
<td>7</td>
<td>Differential pressure sensor’s amplifier</td>
<td>DMD-465WB</td>
<td>x &amp; z axes</td>
<td>(Linearity) ± 0.05% of full scale = ± 0.005 V</td>
</tr>
<tr>
<td>8</td>
<td>Controller board &amp; data acquisition</td>
<td>DS1104R&amp;D</td>
<td>x &amp; z axes</td>
<td>Not Available</td>
</tr>
</tbody>
</table>

3.2 Sensor Calibration

3.2.1 Position Sensor

The calibration of the position sensor was done by moving the piston of the x-axis cylinder to known positions measured by a meter stick and then recording the output voltage. Figure 3-3 shows the curve fitting result for the x-axis. It was found that the position in mm can be calculated as follows:

\[ x = 109.35 r - 41.6 \]  
(3-2)

where \( r \) is the reading in volts from the x-axis position sensor. The coefficient of determination for Equation 3-2 is \( R^2 = 0.99 \).
3.2.2 Velocity Sensor

The calibration of the $x$-axis velocity was done by conducting a series of open loop tests. In order to find the coefficient for converting the velocity signal in volts to its mm/s value, one can take the derivative of the position signal and then divide by the corresponding velocity signal. Thus, the coefficient of velocity ($C_v$) is formulated as follows:

$$C_v = \frac{(\Delta x / \Delta t)}{r}$$

(3-3)

Since the velocity in mm/s which is derived by differentiating the position signal is relatively noisy, a second order Butterworth filter was applied to the position signal. The velocity signal was also filtered.

To obtain the value of $C_v$, three different open loop tests were conducted, as illustrated in Figures 3-4 to 3-6, with three values for the magnitude (+/- 1, +/- 2.5 and +/- 3 volts) and three values for the frequency (0.3, 0.5 and 0.7 Hz) of the square wave control signal. Individual coefficients were obtained for each pulse by dividing the calculated velocity by the measured
velocity (as averaged over the width of the pulse). The average of the individual coefficients gave:

\[
C_v = 323.8 \left( \frac{mm/s}{volt} \right)
\]  

(3.4)

with a standard deviation of \(2.2 \left( \frac{mm/s}{volt} \right)\).

The drift in position, which is most evident in Figure 3-5, is likely due to uneven wear in the cylinder. It also highlights that the friction force is greater in one direction than the other, which adds another degree of nonlinearity to the problem.

![Graphs showing position, control, reading, and velocity over time.](image)

**Figure 3-4** Velocity sensor calibration with \( u = 6 \) and \( 4 \) input voltages
Figure 3-5 Velocity sensor calibration with \( u = 7 \) and 3 input voltages

Figure 3-6 Velocity sensor calibration with \( u = 8 \) and 2 input voltages
3.2.3 Pressure Sensor

In order to calibrate the differential pressure sensor, one port was left open to atmospheric pressure while the other port was connected to the pressure air line. The pressure was increased gradually and the sensor output voltage was recorded at each pressure step. The same sequence was repeated with the connections for the ports reversed. Figure 3-7 shows the curve fitting results for the $x$-axis. It was found that the differential pressure in kPa can be calculated as follows:

$$\Delta P_x = 62.66 \ r - 3.13 \quad (3-5)$$

where $r$ is the reading in volts from the $x$-axis differential pressure sensor. The coefficient of determination for Equation 3-5 is $R^2 = 0.99$.
3.3 Adaptive Neural Network

Background on NNs in general was given in Chapter 2. In this section, details on an Adaptive Neural Network (ANN) will be given including the method of implementation. For the purposes of this thesis, the formulation will be given assuming a three layered NN as illustrated in Figure 2-24.

Lewis et al (1996) developed a multilayer nonlinear NN-based controller for a two-link planar manipulator with electric actuators. The algorithm was originally termed as the Modified Back Propagation Method (MBPM). In MBPM, an improved weight training method was used to correct for deficiencies that result when a NN is implemented with a standard Back Propagation Algorithm (BPA). The proposed training algorithm is able to make the NN strictly state passive such that bounded weights are guaranteed. The strategy for using NN in their work was to use the NN as a feed-forward compensator to negate the nonlinearities and enable a conventional controller to deal with the linearized system.

The MBPM proposed by Lewis et al was adapted to real time control applications and relabeled as an Adaptive Neural Network (ANN) by Campa (2001). He provided a Simulink® block in MATLAB® which models the MBPM defined by the following set of equations. It should be noted that some elements of this section has been taken from the Doctoral thesis of Abu-Malloh (2008).

![Three layer Neural Network with one output](image)

Figure 3-8 Three layer Neural Network with one output
In reference to Figure 2-24 for sigmoidal NNs, the activation function \( \sigma_i \) for node \( i \) in a given layer \( L \) is defined as:

\[
\sigma_i = \frac{1}{1 + e^{-net_i^L}}, \quad i = 1, 2, ..., B^L
\]  

(3-6)

where \( B^L \) is the number of nodes in layer \( L \). The function \( net_i^L \) is the sum of the inputs to node \( i \) in layer \( L \) and is defined for the hidden layer \( (L=2) \) and output layer \( (L=3) \) as follows:

\[
net_i^2 = \sum_{j=1}^{B^1} V_{i,j} p_j + b_i^2, \quad i = 1, 2, ..., B^2
\]  

\[
net_i^3 = \sum_{j=1}^{B^2} W_{i,j} a_j^2 + b_i^3
\]  

(3-7) \hspace{1cm} (3-8)

where \( V_{i,j} \) is the weight connecting node \( i \) in the hidden layer \( (L=2) \) and input \( p_j \) of the input layer, \( p_j \) is \( j^{th} \) input of the input layer, \( W_{i,j} \) is the weight connecting the output node in the output layer and the output of node \( j \) in the hidden layer \( (a_j^2) \) and \( B^2 \) is the number of nodes in the hidden layer. Finally, \( b_i^2 \) and \( b_i^3 \) are the bias of node \( i \) in the hidden and output layer, respectively.

The standard sigmoid activation function given as Equation 3-6 is used as the basis for ANN. For BPA-based NNs, the training algorithm for the weights is given as:

\[
\dot{W} = F \sigma (V^T P) e
\]  

(3-9)

\[
\dot{V} = GP(W^T \dot{\sigma} (V^T P)e)^T
\]  

(3-10)

where \( W \) is the weight vector for the output layer, \( V \) is the weight vector for the hidden layer, \( F \) is the learning rate for \( W \) and \( G \) is the learning rate for \( V \). Finally, \( P \) is the input vector and \( e \) is the error in the input. In MBPM, the training algorithm for the weights is given as:

\[
\dot{W} = F [\sigma (V^T P)e - \dot{\sigma} (V^T P)V^T Pe - \lambda W \|e\|_F]
\]  

(3-11)
\[
\dot{V} = G[P(W^T \dot{\sigma}(V^TP)e)^T - \lambda V\|e\|_F]
\] (3-12)

where \( \lambda \) is a small positive tunable parameter whose function is to help deal with unmodeled dynamics (Lewis et al 1998). Examination of Equations 3-11 and 3-12 reveal that they consist of a standard back propagation term (1st term in equations), plus the error modification term taken from adaptive control (last term), plus a novel second order forward propagation term taken from the back propagation network (2nd term in Equation 3-11).

In ANN the Neural Network output \( u_{NN} \) is given as:

\[
u_{NN} = \sigma \left( \sum_{j=1}^{B^2} (W_{1,j}a_j^2) + b_1^3 + D \right)
\] (3-13)

where an additional parameter \( D \) has been added to the standard NN output to overcome higher order modeling errors. The parameter \( D \) is given by:

\[
D = -K_z \left( \|Z\|_F + \bar{Z} \right)e - K_v e
\] (3-14)

where \( \bar{Z} \) is the maximum expected value of \( Z \), \( K_z \) and \( K_v \) are gain terms and the square matrix \( Z \) is given by:

\[
Z = \begin{bmatrix}
W & 0 \\
0 & V
\end{bmatrix}
\] (3-15)

In Equation 3-14, \( \| \cdot \|_F \) denotes the Frobenius norm and for \( Z \) is defined as:

\[
\|Z\|_F = \sqrt{\text{trace}(Z^*Z)}
\] (3-16)

where \( Z^* \) denotes the conjugate transpose of \( Z \). Trace is defined for a square matrix \( A \) as follows:

\[
\text{trace}(A) = \sum_{i=1}^{n} a_{ii}
\] (3-17)
Figure illustrates a summary of ANN formulation with eight tuning parameters highlighted. These are the tuning parameters that appear literally in the formulation. Those are not seen in the formulation belong to the ANN MATLAB® toolbox settings. All thirteen tuning parameters are given in Table 3-3.

\[ u_{NN} = \sigma \left( \sum_{j=1}^{B_2} (W_{1,j} a_j^2) + b_1^3 + D \right) \]

The advantage of ANN is that it is designed expressly for online training. Thus, the weights can be easily initialized and trained online. No off-line training is required. The ANN tuning algorithm makes the NN strictly state passive. This means that bounded weights are guaranteed for all applications, even in the presence of unmodeled disturbances and dynamics.

\[ D = -\mathcal{K}_f \left\| Z \right\|_F - \mathcal{Z} e - \mathcal{K}_e \]

Frobenius norm:
\[ Z = \begin{bmatrix} W & 0 \\ 0 & V \end{bmatrix} \]
\[ \left\| Z \right\|_F = \sqrt{\text{trace}(Z^T Z)} \]
\[ K_f \] and \[ K_e \] are tunable parameters

\[ net_i^3 = \sum_{j=1}^{B_1} W_{1,j} a_j^2 + b_1^3 \]
\[ net_i^1 = \sum_{j=1}^{B_3} V_{1,j} P_j + b_1^2 \]

\[ \dot{V} = G P (W^T \dot{\sigma} (V^T P)e) = -\dot{\lambda} \left\| e \right\|_F \]
\[ \dot{W} = F \sigma (V^T P)e - \dot{\sigma} (V^T P)V^T Pe - \lambda W \left\| e \right\|_F \]

\[ \sigma_i = \frac{1}{1 + e^{-net_i}} \] for each layer, \( i = 1, 2, ..., B \)

\[ \sigma \]: Activation Function

Figure 3-9 ANN formulation with selected tuning parameters highlighted

The advantage of ANN is that it is designed expressly for online training. Thus, the weights can be easily initialized and trained online. No off-line training is required. The ANN tuning algorithm makes the NN strictly state passive. This means that bounded weights are guaranteed for all applications, even in the presence of unmodeled disturbances and dynamics.
3.3.1 ANN Implementation

This section presents the ANN Simulink® block used in this thesis, as originally developed by Campa (2001). Figure 3-10 shows the Simulink® block diagram for the position controller used in Chapter 5 with the ANN input/output (I/O) block highlighted. In this example, the output of the ANN I/O block is added to the output of a PID controller and an $\Delta P$ feedback block.

Figure 3-11 details the ANN input/output block highlighted in Figure 3-10. For this position control example, the input vector is seen to have 4 inputs: $x, e, v,$ and $\Delta P$. All of the inputs must have the same dimension. Since the control signal is in volts, all the inputs have to be expressed in volts.

Figure 3-12 details the ANN model block highlighted in Figure 3-11. This model block is the Simulink® implementation of Equations 3-6 to 3-15.

Table 3-3 gives the ANN model block parameters. These tunable parameters are adjusted with the Graphical User Interface (GUI) shown in Figure 3-13. In addition to the ANN parameters, the initial weights ($V, W$) and sampling time ($h$) must be entered by the user. The sampling time is set to 1 msec, the same sample time used by the dSPACE/DSP data acquisition board.

It was found that the nature and number of the inputs can affect the results. For example, it was found that the number of inputs could be reduced to 10, without losing performance (default value is 30). This improves the computational efficiency. Furthermore, it was found that if the numbers of inputs was greater than 15, then MATLAB® was unable to compile.
Figure 3-10 Simulink® block diagram for position controller with ANN I/O block highlighted

Figure 3-11 Detail of ANN I/O block labeled in Figure 3-10
Figure 3-12 Detail of ANN model block labeled in Figure 3-11 with key input/outputs circled (Campa, 2008)
Figure 3-13 Screen capture of input parameters page for the ANN model block (Campa, 2008)

Table 3-3 ANN model block parameters (Campa, 2008)

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter</th>
<th>Definition</th>
<th>Default value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$n_i$</td>
<td>number of inputs</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>$n_h$</td>
<td>number of nodes in hidden layer</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>$n_o$</td>
<td>number of outputs</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>$G$</td>
<td>learning rate of $V$</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>$F$</td>
<td>learning rate of $W$</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>$\lambda$</td>
<td>adaptation parameter</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>$s$</td>
<td>slope of sigmoid activation function</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>$bias$</td>
<td>activation function bias</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>$V_{Lim}$</td>
<td>limit of $V$</td>
<td>1 e37</td>
</tr>
<tr>
<td>10</td>
<td>$W_{Lim}$</td>
<td>limit of $W$</td>
<td>1 e37</td>
</tr>
<tr>
<td>11</td>
<td>$K_z$</td>
<td>tunable parameter</td>
<td>0</td>
</tr>
<tr>
<td>12</td>
<td>$K_v$</td>
<td>tunable parameter</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>$Z$</td>
<td>tunable parameter</td>
<td>0</td>
</tr>
</tbody>
</table>
Regarding the implementation of the ANN block, the block is compiled by MATLAB® to generate a C file useable by dSPACE (the controller board). It was found that MATLAB® 2007a was not compatible with dSPACE 6.0 and MATLAB® could not compile the Simulink® file (result was a running error). This problem was corrected when MATLAB® was updated to 2009a and dSPACE was updated to 6.3. After these changes, the Simulink® program could be compiled and the respective C file generated.

### 3.3.2 ANN Tuning Procedure

For the most part, the tuning of a NN is accomplished in an ad hoc fashion. Based upon experience with the application of ANN for this thesis, a more formal tuning procedure has been developed. The procedure is illustrated in Figure 3-14 and can be broken into three steps. The variables were previously defined in Table 3-3.

#### Step 1: Initialization

The first step involves initializing those parameters that relate to the basic design of any NN. Given that there is only one output, \( n_o \) is set to 1. The number of inputs (nodes in the input layer) is one of the key design variables for the structure of the NN. For this thesis, \( n_i \) is 10 for velocity control and 12 for position control. The choice of \( n_i \) will be discussed in Chapters 4 and 5 for velocity and position, respectively. In order to set the number of nodes in the hidden layer, one should increment \( n_h \) initially by 5. Once the change in performance is noticeable, \( n_h \) should be varied by \( \pm 2 \) until the response is satisfactory. Increasing the value of \( n_h \) beyond this point only serves to increase the processing time. In addition, MATLAB® is unable to compile the program if \( n_i \) and \( n_h \) are set too high. The upper limit for compiling was found to be difficult to predict.

It was found that \( S \) and \( bias \) could be set to 1 without affecting the results. The weight limits \( V_{lim} \) and \( W_{lim} \) were set to 10. These limits can be viewed as analogous to saturation limits for a control signal. Thus, to confirm whether they are initialized correctly, one can monitor \( V \) and \( W \) as the ANN runs to ensure that the weights don’t saturate unexpectedly.
**Step 2: Coarse Tuning**

In the second step, one does coarse tuning which involves $G$, $F$ and $\lambda$. It was found that, high $G$ and $F$ enables one to use high $\lambda$. According to the tests, both $G$ and $F$ can be set to the same value. Thus, they can be treated as one parameter called $GF$. It is recommended that changes in $GF$ and $\lambda$ be no more than $\pm 50\%$ from their default value of 1. However, if there is no noticeable change in the tracking, they can be increased up to a value of 3. Once tracking performance is considered reasonably acceptable in terms of the amount of steady-state error, degree of oscillation, and settling time; one can go to the next step.

**Step 3: Fine Tuning**

In the third and final step, one does fine tuning which involves $K_z$, $K_v$ and $\bar{Z}$. Setting all three to the same value was found to work. Thus, they can be treated as one parameter called $KKZ$. Based upon experience with the ANN block, one should increment $KKZ$ by 0.1. Once the change in performance is noticeable, $KKZ$ should be varied by $\pm 0.01$ until the response is satisfactory.

**3.4 Summary**

This chapter provided background on the apparatus including sensor calibration. Details on the Adaptive Neural Network (ANN) were also given including the implementation in Simulink®.

In the next two chapters, the apparatus will be used to obtain results for the cases of velocity control and position control, with a view to evaluating the performance of ANN as applied to one axis of the gantry crane as a pneumatic system.
Chapter 4

Velocity Control and ANN

In this chapter the apparatus is used to obtain results for the case of velocity control, with a view to evaluating the performance of an Adaptive Neural Network (ANN) as applied to one axis of the gantry robot as a pneumatic system. Seven different controllers are tested and their performance compared: 1) P-only, 2) PI, 3) PI+ΔP, 4) ANN, 5) ANN+ΔP, 6) P-only+ANNC (ANN compensator) and 7) PI+ANNC. For ANN and ANN+ΔP, ANN is applied as a stand-alone controller. For P-only+ANNC and PI+ANNC, ANN is applied as a compensator.

4.1 PID Velocity Controllers

The first controllers to be considered are a Proportional (P-only), Proportional plus Integral (PI) velocity and Proportional plus Integral plus Derivative (PID) controllers. Figure 4-1 shows the block diagram.

\[ u = K_p e_v + K_i \int e_v dt + K_d \frac{de_v}{dt} \]  \hspace{1cm} (4-1)

\[ e_v = v_s - v \]  \hspace{1cm} (4-2)

where \( e_v \) is the velocity error, \( v_s \) is the velocity setpoint; \( K_p, K_i \) and \( K_d \) are the proportional, integral and derivative gains, respectively. In this chapter, the velocity signal is not filtered.
Three proportional gains were examined in order to find the best performance for the P-only controller. Figure 4-2 gives the P-only velocity controller result for three gains ($K_p = 1, 2$ and $6$). As expected, the steady-state error gets smaller and the degree of oscillation increases as the gain is increased. The value $K_p = 2$ is considered tuned in terms of balancing reasonable steady-state error, acceptable degree of oscillation and a relatively short settling time.

Figure 4-3 gives the same result as for Figure 4-2 except on a shorter time scale in order to highlight the lag introduced at low gains. Although there is no delay in the control signal in response to the change setpoint for all three gains, there is a delay or dead time on the order of $0.2 \, \text{s}$ for the case of $K_p = 1$. This is due to the time taken to charge the cylinder with pressurized air before movement is possible which is most visible at low gains.
Figure 4-3 Close-up of Figure 4-2 to show the effect of gains on the delay

Figure 4-4 gives the PI velocity controller result for three integral gains ($K_i = 2, 8$ and $16$) with $K_p$ set to 2. The PI controller with $K_p = 2$ and $K_i = 8$ is considered tuned in terms of balancing reasonable steady-state error on the order of $\pm 15$ mm/s, acceptable degree of oscillation and a relatively short settling time. The PI controller with $K_i = 16$ is considered to be untuned due to excessive oscillation.

Figure 4-5 shows the comparison of the tests results with tuned P-only and PI controllers. According to the figure, the PI controller is able to reduce the steady-state error. Table 4-1 gives the summary of the tuned P-only and PI controller gains. Results are not presented for PID velocity control as it was found that derivative action did nothing to improve the performance.

Table 4-2 gives a comparison of the tuned velocity control results of this thesis to the ones presented in Abu-Mallouh and Surgenor (2007) in which they used PPC valves to control the same pneumatic cylinder. They also used a PI controller for their study. The time intervals of both cases are relatively the same ($2$ s). Results are compared when the system has reached equilibrium. According to the table, the percentage of undershoot and overshoot in Abu-Mallouh and Surgenor (2007) is relatively high. Also, the setting time and delay values are higher than
those of this thesis. It should be noted that in PFC valves are used in this thesis which have faster response time than PPC valves. However, in terms of steady-state error, Abu-Mallouh and Surgenor reported better performance with their PPC valves. The reader is reminded that despite the slower response of PPC valves, they are easier to control than PFC valves.

Table 4-1 Summary of tuned P-only and PI controller gains

<table>
<thead>
<tr>
<th>Type of Controller</th>
<th>$K_p$</th>
<th>$K_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-only</td>
<td>2</td>
<td>N/A</td>
</tr>
<tr>
<td>PI</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>Abu-Mallouh and Surgenor (2007)</td>
<td>0.5</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 4-2 Comparison of tuned velocity control results, this thesis and Abu-Mallouh and Surgenor (2007)

<table>
<thead>
<tr>
<th>Case</th>
<th>Steady-state error (mm/s)</th>
<th>Percentage overshoot (%)</th>
<th>Percentage undershoot (%)</th>
<th>Settling time (s)</th>
<th>Delay (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>This thesis</td>
<td>± 15</td>
<td>N/A</td>
<td>N/A</td>
<td>0.4</td>
<td>0.04</td>
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<tr>
<td>Abu-Mallouh and Surgenor (2007)</td>
<td>± 10</td>
<td>8</td>
<td>83</td>
<td>0.7</td>
<td>0.1</td>
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</table>
Figure 4-4 PI velocity controller result for three integral gains

Figure 4-5 Comparing P-only and PI velocity controllers
4.1.1 PI plus $\Delta P$ Velocity Controller

The next controller to be studied is PI+$\Delta P$. The block diagram of the velocity controller is illustrated in Figure 4-6. This section investigates the effect of $\Delta P$ on the PI controller. In practice, acceleration feedback is normally avoided as the signal tends to be noisy. An alternative is to use the cylinder differential pressure as an indirect measure of acceleration.

Basically, $\Delta P$ adds damping to the system. It is best seen when the response without $\Delta P$ is fairly oscillatory. Thus, the effect of $\Delta P$ is demonstrated for an untuned PI ($K_p = 2$, $K_i = 16$) controller response.

Figure 4-7 illustrates the effect of $\Delta P$ on a PI controller with untuned integral gain. It can be observed that adding $\Delta P$ to the system results in lower oscillations. Also in the figure, the differential pressure of the cylinder is shown. This parameter can be very helpful to monitor the effect of friction on the system.

In a linear pneumatic system, for a cylinder to be stationary ($v = 0$) the differential pressure must be zero. However, for a nonlinear system that includes friction, the differential pressure will be non-zero to counteract the force friction. This is illustrated in Figure 4-7
4.2 ANN as a Velocity Controller

The third controller to be studied in this section is an ANN stand-alone velocity controller. The background on ANN and tuning procedures were given in Chapter 3.

In Figure 4-8 the block diagram of the NN controller is shown. As shown in the figure, $V_s$, $e_v$ and $V$ are used as primary inputs to the ANN block. There are ten secondary inputs which are created from these three primary inputs. These secondary inputs are illustrated in Figure 4-9.

Figure 4-10 gives the tuned ANN1 controller start-up response in order to show the pressure equilibrium dynamics. One should note the slow rise in $P_a$ and $P_b$ until they reach equilibrium values on the order of $300 \text{ kPa} \pm 20 \text{ kPa}$ after four cycles.
Figure 4-8 Block diagram of the ANN velocity controller with three primary inputs

\[
\begin{align*}
\nu(t) \\
\nu(t-1) \\
\nu(t-2) \\
\nu(t-3) \\
e_v(t) \\
e_v(t-1) \\
e_v(t-2) \\
\nu_s(t) \\
\nu_s(t-1) \\
\nu_s(t-2)
\end{align*}
\]

\[u_{NN}\]

Figure 4-9 Input vector with ten secondary inputs for the ANN block
In Figure 4-11, the weight equilibrium dynamics of the ANN1 are illustrated. \( V \) and \( W \) have 100 and 10 elements, respectively (refer to Figure 3-8). For each of \( V \) and \( W \), two weights are selected to be shown (namely \( V_{1}, V_{71} \) and \( W_{1}, W_{2} \)) in order to illustrate the different dynamics of the weights. As shown in the figure, the weights reach equilibrium within two cycles.

One should note that Figures 4-12 to 4-15 show the system when it is in equilibrium. Thus, except for Figure 4-10 and Figure 4-11, all tests start after the cylinder has been cycled five times just to make sure that they have reached equilibrium.

Two different tunings are presented for the ANN stand-alone velocity controller, each of which has its own advantages. The set of parameters for ANN1 and ANN2 are given in Tables 4-2 and 4-3, respectively. Extensive work was done to tune the ANN block. Although the tuning procedure for a NN is normally ad hoc, a more formal tuning procedure was presented for the ANN in Chapter 3. It involved three steps: default (initialization), coarse tuning and fine tuning.

Figure 4-12 and Figure 4-13 illustrate the tracking performance with default, coarse and fine tuned parameters for the ANN1 and ANN2 controllers, respectively. In both cases coarse tuning is seen to be comparable with the fine tuning in terms of setpoint tracking and steady-state error. One of the characteristics of the ANN controller appears to be the saturation in the control signal (between 4 to 6 volts) which is most evident in Figure 4-13.

Figure 4-14 provides a direct comparison of ANN1 versus ANN2. ANN2 is considered to show better performance in comparison with ANN1 in terms of less overshoot and less delay in the velocity signal. As labeled in the figure, ANN1 has a delay in the velocity signal on the order of 0.35 s. Also, in both responses one is able to see the friction effect which results in a drift in the differential pressure of the cylinder.

The responses for the P-only, PI and ANN1 controllers are compared in Figure 4-15. ANN1 does a fairly good job in compensating for the steady-state error with faster settling time. However, ANN1 fails to reduce the overshoot and also has a fairly large delay.

Quantitative performance comparison of the controllers presented in this chapter will be given in Section 4.4.
Figure 4-10 ANN1 velocity controller, system start-up to show pressure equilibrium dynamics

Figure 4-11 ANN1 velocity controller, system start-up to show equilibrium dynamics of selected weights

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### Table 4-3 ANN1 controller, tuned parameters

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter</th>
<th>Definition</th>
<th>Default value</th>
<th>Coarse Tuning</th>
<th>Fine Tuning</th>
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<td>1</td>
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<td>$F$</td>
<td>learning rate of $W$</td>
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<td>2</td>
<td>1.5</td>
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<td>$s$</td>
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<td>1</td>
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<td>0</td>
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<td>$Z$</td>
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### Table 4-4 ANN2 controller, tuned parameters

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<td>10</td>
<td>$W_{Lim}$</td>
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<td>10</td>
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<td>$K_v$</td>
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<td>0.1</td>
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<td>$Z$</td>
<td>tunable parameter</td>
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<td>0.1</td>
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Figure 4-12 ANN1 velocity controller result with default, coarse and fine tuning

Figure 4-13 ANN2 velocity controller result with default, coarse and fine tuning
Figure 4-14 Comparison of ANN1 and ANN2 tuned velocity controller results

Figure 4-15 Comparison of PI, P-only and ANN1 tuned velocity controller results
4.2.1 ANN plus ΔP Velocity Controller

In the previous section, the ANN stand-alone controller was introduced. Two different ANN tunings were tested (ANN1 and ANN2). In this section, the effect of adding ΔP to these controllers is presented. Inputs to the ANN block remain unchanged. Figure 4-16 shows the block diagram of ANN+ΔP velocity controller.

Figure 4-17 and Figure 4-18 illustrate the response of ANN1+ΔP and ANN2+ΔP, respectively. Three differential pressure gains were examined for each of ANN1 and ANN2. For ANN1 the tuned differential pressure gain is $K_{\Delta P} = 0.1$ and for ANN2, it is $K_{\Delta P} = 0.07$. In both cases, adding ΔP resulted in lower overshoot and reduced oscillations. However, steady-state error increases.

Figure 4-17 shows that the delay in velocity increases from 0.25 to 0.5 s when $K_{\Delta P} = 1$. However, this is not the case for ANN2. According to Figure 4-18, $K_{\Delta P} = 0.2$ and $K_{\Delta P} = 0$ have roughly the same level of delay (0.1 s).

In conclusion, ΔP is able to lower the level of oscillations. In both tests with ANN1 and ANN2, higher ΔP gains led to higher steady-state error. However, it terms of delay, increasing the ΔP gain had different effects. For ANN1, it increased the amount of delay but for ANN2 it had minimal effect on delay.

![Figure 4-16 Block diagram of the ANN+ΔP velocity controller](image)
Figure 4-17 ANN1+ΔP velocity controller results for three ΔP gains

Figure 4-18 ANN2+ΔP velocity controller results for three ΔP gains
4.3 ANN as a Compensator for Velocity Control

In the previous section, ANN was employed as a stand-alone controller. In this section, ANN will be used as a compensator operating in parallel with a PI controller. This is illustrated in Figure 4-19 where the NN signal is added to the conventional controller signal. The structure of the ANN compensator (ANNC) block remains unchanged. Thus, $v_s$, $e$, and $V$ remain as the primary inputs to the ANNC block.

The role of the ANNC is to help linearize the system in order to improve the performance of the PID controller. Specifically, as an online adaptive compensator, it seeks to negate friction and other nonlinear effects inherent in the pneumatic system (Choi et al, 1998).

![Figure 4-19 Block diagram of the PI+ANNC velocity controller](image)

Figure 4-20 shows the result for the tuned P-only velocity controller with and without ANNC. ANNC is seen to do a relatively good job in compensating for the steady-state error. However, a certain amount of delay is added to the response on the order of 0.15 s. Figure 4-21 gives the result for the tuned PI velocity controller with and without ANNC. In contrast to the improvement made by ANNC to P-only control, adding ANNC does not make the PI setpoint tracking any better.

In Figure 4-22 and Figure 4-23, one is able to see the effect of tuning the ANNC on performance for the P-only and PI velocity controllers, respectively. Three sets of parameters were applied: default values, coarse tuning and fine tuning. Figure 4-22 shows that default ANN values are ineffective. The coarse tuning is seen to be fairly close to the fine tuning result for both Figure 4-22 and Figure 4-23. The ANNC parameters are given in Table 4-5 and Table 4-6.
One should note that the tuning procedure presented in Chapter 3 was followed consistently for position control (Chapter 5). However, for velocity control (this chapter) the tuning procedure was slightly modified. According to the presented tuning procedure, $K_v, K_z$ and $\bar{Z}$ should have the same value ($KKZ$). However, in Table 4-5, one sees that it is not the case ($K_z = 1.5$, $K_v = 0$, $\bar{Z} = 0$). The formal ANN tuning procedure was fully developed for the position control after velocity control was complete. Thus, Table 4-5 was considered to be relatively inconsistent with the tuning procedure.

Figure 4-24 shows the result for the untuned P-only ($K_p = 1$) velocity controller with and without ANNC. ANNC is seen to do a relatively good job in reducing the steady-state error but at the cost of increased oscillations. The ANNC parameters for this case are given in Table 4-7.

Figure 4-25 shows the result for the untuned PI ($K_p = 2$, $K_i = 2$) velocity controller with and without ANNC. ANNC is seen to do a relatively good job in reducing the steady-state error. The ANNC parameters for this case are given in Table 4-8.
### Table 4-5 P-only+ANNC – tuned parameters

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<tr>
<th>No.</th>
<th>Parameter</th>
<th>Definition</th>
<th>Default value</th>
<th>Coarse Tuning</th>
<th>Fine Tuning</th>
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<tbody>
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<td>1</td>
<td>$n_i$</td>
<td>number of inputs</td>
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<td>10</td>
<td>10</td>
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<td>1.1</td>
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<td>1</td>
<td>1</td>
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<tr>
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<td>limit of $W$</td>
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### Table 4-6 PI+ANNC – tuned parameters

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Table 4-7 Untuned P-only+ANNC – tuned parameters

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<td>bias</td>
<td>activation function bias</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>$V_{Lim}$</td>
<td>limit of $V$</td>
<td>$1 \times 10^37$</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>$W_{Lim}$</td>
<td>limit of $W$</td>
<td>$1 \times 10^37$</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>11</td>
<td>$K_z$</td>
<td>tunable parameter</td>
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<td>0</td>
<td>0.1</td>
</tr>
<tr>
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<td>$K_r$</td>
<td>tunable parameter</td>
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<td>0</td>
<td>0.1</td>
</tr>
<tr>
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<td>$Z$</td>
<td>tunable parameter</td>
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<td>0.1</td>
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</tbody>
</table>

Table 4-8 Untuned PI+ANNC – tuned parameters

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter</th>
<th>Definition</th>
<th>Default value</th>
<th>Coarse Tuning</th>
<th>Fine Tuning</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$n_i$</td>
<td>number of inputs</td>
<td>30</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>$n_h$</td>
<td>number of nodes in hidden layer</td>
<td>2</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>$n_o$</td>
<td>number of outputs</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>$G$</td>
<td>learning rate of $V$</td>
<td>1</td>
<td>1</td>
<td>2.5</td>
</tr>
<tr>
<td>5</td>
<td>$F$</td>
<td>learning rate of $W$</td>
<td>1</td>
<td>1</td>
<td>2.5</td>
</tr>
<tr>
<td>6</td>
<td>$\lambda$</td>
<td>adaptation parameter</td>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>$s$</td>
<td>slope of sigmoid activation function</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>bias</td>
<td>activation function bias</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>$V_{Lim}$</td>
<td>limit of $V$</td>
<td>$1 \times 10^37$</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>$W_{Lim}$</td>
<td>limit of $W$</td>
<td>$1 \times 10^37$</td>
<td>10</td>
<td>10</td>
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<td>$K_z$</td>
<td>tunable parameter</td>
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<td>0</td>
<td>0.001</td>
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<tr>
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<td>$K_r$</td>
<td>tunable parameter</td>
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<td>0</td>
<td>0.001</td>
</tr>
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<td>13</td>
<td>$Z$</td>
<td>tunable parameter</td>
<td>0</td>
<td>0</td>
<td>0.001</td>
</tr>
</tbody>
</table>
Figure 4-20 Tuned P-only velocity controller with and without ANNC results

Figure 4-21 Tuned PI velocity controller with and without ANNC results
Figure 4-22 Tuned P-only+ANNC velocity controller default, coarse and fine tunings

Figure 4-23 Tuned PI+ANNC velocity controller default, coarse and fine tunings
Figure 4-24 Untuned P-only velocity controller with and without ANNC results

Figure 4-25 Untuned PI velocity controller with and without ANNC results
4.4 Quantitative Performance Comparison

In this section, a quantitative comparison of the performance of the seven controllers will be presented. Three quantitative measures will be used, namely percentage overshoot, percentage undershoot and the calculated Root Mean Square Error (RMSE):

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N}(error)^2}{N}} \tag{4-3}
\]

Also, the improvement in tracking performance is measured by the change in \(RMSE (\Delta RMSE_i)\) which is calculated as follows:

\[
\Delta RMSE_i = \frac{RMSE_i - RMSE_{ref}}{RMSE_{ref}} \times 100 \tag{4-4}
\]

where \(N\) is the number of samples and \(RMSE_{ref}\) denotes the \(RMSE\) of the reference signal. A negative \(\Delta RMSE\) means an improvement in performance (i.e. tracking error reduced).

Table 4-9 provides a comparison of the tracking performances for the controllers used in this chapter. The key results for \(RMSE\) are color coded: red for the worst, yellow for the second best and green for the best result. In terms of reducing the \(RMSE\) , tuned PI has the best performance (\(RMSE\) drops by 45%, relative to the tuned P-only result). The second best performance is the untuned PI+ANNC. The positive effect of ANNC is best seen by comparing the untuned PI result without ANNC (\(RMSE\) drops by 11%) to that with ANNC (\(RMSE\) drops by 38%). This supports using ANNC to compensate for an untuned controller.

ANN1 degrades performance (\(RMSE\) increases by 11%). But this can be improved by the addition of \(\Delta P\) feedback (\(RMSE\) increases by only 2%). Finally, ANN2 is better than ANN1 (\(RMSE\) drops by 16%), but again neither is as good as tuned PI.

In terms of reducing the overshoot and undershoot, adding \(\Delta P\) reduces the overshoot and undershoot for the ANN1 controller from 28% and 34% without \(\Delta P\), to 14% and 22% with \(\Delta P\), respectively. It is noted that the untuned PI+ANNC result has relatively high overshoot and undershoot (43% and 38%). If this is considered to be a problem, adding \(\Delta P\) feedback would be an option to reduce the overshoot and undershoot.
Gross and Rattan (1997) reported a 81% reduction in RMSE for PID with a NN compensator for velocity control with a pneumatic cylinder. But this was a simulation result, the NN was trained offline and they worked at twice the speed (500 mm/s) with what appears to be a low-friction cylinder. Working at higher speeds can lower the effect of Coulomb friction.

Table 4-9 Performance with different velocity controllers, with key values highlighted

<table>
<thead>
<tr>
<th>Controller Type</th>
<th>Figure No.</th>
<th>Overshoot (%)</th>
<th>Undershoot (%)</th>
<th>RMSE (mm/sec)</th>
<th>ΔRMSE(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>untuned P-only ($K_p = 1$)</td>
<td>4-2</td>
<td>N/A</td>
<td>N/A</td>
<td>138</td>
<td>55</td>
</tr>
<tr>
<td>tuned P-only ($K_p = 2$)</td>
<td>4-2</td>
<td>14</td>
<td>31</td>
<td>89</td>
<td>reference</td>
</tr>
<tr>
<td>untuned PI ($K_p = 2$, $K_i = 2$)</td>
<td>4-4</td>
<td>N/A</td>
<td>N/A</td>
<td>79</td>
<td>-11</td>
</tr>
<tr>
<td>tuned PI ($K_p = 2$, $K_i = 8$)</td>
<td>4-4</td>
<td>18</td>
<td>20</td>
<td>49</td>
<td>-45</td>
</tr>
<tr>
<td>ANN1</td>
<td>4-14</td>
<td>28</td>
<td>34</td>
<td>99</td>
<td>11</td>
</tr>
<tr>
<td>ANN1+ΔP</td>
<td>4-17</td>
<td>14</td>
<td>22</td>
<td>91</td>
<td>2</td>
</tr>
<tr>
<td>ANN2+ΔP</td>
<td>4-18</td>
<td>2</td>
<td>25</td>
<td>79</td>
<td>-12</td>
</tr>
<tr>
<td>ANN2</td>
<td>4-14</td>
<td>13</td>
<td>26</td>
<td>75</td>
<td>-16</td>
</tr>
<tr>
<td>untuned P-only ($K_p = 1$) + ANNC</td>
<td>4-24</td>
<td>49</td>
<td>49</td>
<td>70</td>
<td>-20</td>
</tr>
<tr>
<td>tuned P-only+ ANNC</td>
<td>4-20</td>
<td>25</td>
<td>22</td>
<td>69</td>
<td>-22</td>
</tr>
<tr>
<td>untuned PI ($K_p = 2$, $K_i = 2$) + ANNC</td>
<td>4-25</td>
<td>43</td>
<td>38</td>
<td>55</td>
<td>-38</td>
</tr>
</tbody>
</table>
4.5 Summary

In this chapter the apparatus was used to obtain results for the case of velocity control, with a view to evaluate the performance of Adaptive Neural Network (ANN) as applied to one axis of the gantry robot as a pneumatic system. Seven different controllers were tested and their performance compared: 1) P-only, 2) PI, 3) PI+ΔP, 4) ANN, 5) ANN+ΔP, 6) P-only+ANNC (ANN compensator) and 7) PI+ANNC. For ANN and ANN+ΔP, ANN was applied as a stand-alone controller. For P-only+ANNC and PI+ANNC, ANN was applied as a compensator.

Highlights from this chapter can be stated as:

- ΔP adds damping to the system. Thus, ΔP can lower the degree of oscillation.
- The performance of ANN as a stand-alone controller was comparable to that of a P-only controller.
- Overall, PI showed the best performance among the controllers examined.
- The positive effect of ANNC was best seen by comparing the untuned PI result with and without ANNC.

In the next chapter, position control of the pneumatic system will be examined, as applied to both step and sinusoidal inputs. Based upon the experience gained with velocity control, only two controllers will be examined for position control: PID and PID+ANNC.
Chapter 5

Position Control and ANN

This chapter examines the application of an Adaptive Neural Network Compensator (ANNC) to position control of a pneumatic system, namely one axis of the gantry robot. It provides the tuning methodology and comparative performance results. Two controllers are examined: 1) PID and 2) PID+ANNC. The controllers are tuned for step changes in the setpoint. Then their performance is evaluated as applied to sinusoid tracking.

5.1 PID Position Controllers

The first controllers to be considered are a Proportional (P-only), Proportional plus Integral (PI) velocity and Proportional plus Integral plus Derivative (PID) controllers. Figure 5-1 illustrates the block diagram of the PID position controller.

For the PID position controller, the control signal $u$ is given by:

$$u = K_p e_x + K_i \int e_x dt + K_d \frac{de_x}{dt}$$

(5-1)

The PID position control law is the same as that for the PID velocity control (Equation 4-1) except for the error term which is defined as:

$$e_x = x_s - x$$

(5-2)
The controller is tuned with a step test, as detailed in the next section. Since there was a fairly high level of noise in the measured signal that would be picked up by the derivative action, a first order filter was applied to the position signal. The design of the filter is covered in Appendix B.

5.2 PID Tuning Procedure

The tuning procedure for the PID controller employed a step in the setpoint with a 250 mm step size applied at 2 s intervals, as illustrated in Figure 5-2. This repeated step signal mimics a sinusoidal signal with frequency of 0.125 Hz (0.75 rad/s). Tuning with a step in the setpoint then testing on sinusoidal setpoint is a fairly common approach to the tuning of a PID controller when applied to sinusoid tracking. Taghizadeh et al (2010) used the alternate approach which was to both tune and test with sinusoidal signals.

Initial estimates of the PID gains were obtained with the tuning method of Ziegler-Nichols (Z/N) (Ogata, 1997). Table 5-1 summarizes the Z/N tuning rules, where the gains are calculated from the measured values of the critical gain $K_{cr}$ and critical period $P_{cr}$. The proportional gain $K_p$ was increased until the system was in sustained oscillation. This test yielded values of 4.0 and 0.6 s for $K_{cr}$ and $P_{cr}$, respectively. These values in turn gave the calculated initial PID gains given in Table 5-2.

These gains were then retuned to give a reasonable steady-state error, an acceptable degree of oscillation and a relatively short settling time.

<table>
<thead>
<tr>
<th>Type of Controller</th>
<th>$K_p$</th>
<th>$K_i$</th>
<th>$K_d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>$0.5 K_{cr}$</td>
<td>$\infty$</td>
<td>0</td>
</tr>
<tr>
<td>PI</td>
<td>$0.45 K_{cr}$</td>
<td>$\frac{1}{1.2 P_{cr}}$</td>
<td>0</td>
</tr>
<tr>
<td>PID</td>
<td>$0.6 K_{cr}$</td>
<td>$0.5 P_{cr}$</td>
<td>$0.125 P_{cr}$</td>
</tr>
</tbody>
</table>

Table 5-1 Z/N initial estimates as calculated from critical gain $K_{cr}$ and critical period $P_{cr}$
Table 5-2 Z/N initial estimates and retuned PID gains

<table>
<thead>
<tr>
<th>PID Gain Set</th>
<th>$K_p$</th>
<th>$K_i$</th>
<th>$K_d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Z/N</td>
<td>2.4</td>
<td>0.3</td>
<td>0.07</td>
</tr>
<tr>
<td>Retuned</td>
<td>2.2</td>
<td>0.3</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Figure 5-2 gives the Proportional only (P-only) result with $K_p = 2$. The spots circled show the absolute position steady-state error in mm. Figure 5-3 illustrates the result of the PID controller with the retuned gains from Table 5-2.

In comparing Figure 5-2 and Figure 5-3, PID is seen to be able to reduce the average steady-state error from 18.5 mm to 4.6 mm, a 75% reduction. Table 5-3 provides further quantitative performance measures for P-only and PID controllers for step tracking. Thus, the performance with PID is significantly better than performance with P-only.

Table 5-3 Comparison of P-only and PID controller performances

<table>
<thead>
<tr>
<th>Type of Controller</th>
<th>Average steady-state error (mm)</th>
<th>Percentage overshoot (%)</th>
<th>Percentage undershoot (%)</th>
<th>Settling time (s)</th>
<th>Delay (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-only</td>
<td>18.5</td>
<td>8</td>
<td>10</td>
<td>0.7</td>
<td>0.08</td>
</tr>
<tr>
<td>PID</td>
<td>4.6</td>
<td>6</td>
<td>3</td>
<td>0.5</td>
<td>0.06</td>
</tr>
</tbody>
</table>
Figure 5-2 P-only position controller result with 250 mm step size at 2 s intervals

Figure 5-3 PID position controller result with 250 mm step size at 2 s intervals
5.2.1 Sinusoid Tracking with Step Tuning

As discussed in the previous section, the PID controller was tuned for a position setpoint with 250 mm step size at 2 s intervals. In this section, the same PID controller was applied to sinusoid tracking with frequencies of 0.1, 0.2 and 0.5 Hz (0.6, 1.3 and 3.1 rad/s).

Figure 5-4 shows the PID position controller result for a 0.1 Hz sinusoid. Position error, position and control signals are plotted. Figure 5-5 illustrates the PID position controller result for a 0.2 Hz sinusoid. Figure 5-6 gives the PID position controller result for a 0.5 Hz sinusoid.

One is able to see from the figures that the lower the frequency (slower motion) the better the position control. Quantitatively, the error ranges ±50 mm at 0.1 Hz to an error of almost ±200 mm at 0.5 Hz.

![Figure 5-4 PID position controller result, 0.1 Hz sinusoid tracking (500 ± 300 mm amplitude)](image-url)
Figure 5-5 Position PID control, 0.2 Hz sinusoid tracking (500 ± 300 mm amplitude)

Figure 5-6 Position PID control, 0.5 Hz sinusoid tracking (500 ± 300 mm amplitude)
5.3 ANN as a Compensator for Position Control

Background on NNs in general was given in Chapter 2. Also in Chapter 3, details on an Adaptive Neural Network (ANN) were covered including the method of implementation. For the purposes of this thesis, the formulation was given assuming a three layered NN as illustrated in Figure 3-8. In this section, ANN will be used as a compensator operating in parallel with a PID controller.

As stated in Chapter 4, the role of the ANN compensator (ANNC) is to help linearize the system in order to improve the performance of the PID controller. Specifically, as an online adaptive compensator, it seeks to negate friction and other nonlinear effects inherent in the pneumatic system (Choi et al, 1998).

Figure 5-7 gives the block diagram of PID controller with ANNC while demonstrating the reference set of inputs to the ANNC block \( P = [x, x_x, e, v] \). The NN signal is subtracted from the PID output and the difference provides the input signal to the control valve. Based on this diagram the control law would be as follows:

\[
 u = K_p e_x + K_i \int e_x \, dt + K_d \frac{de_x}{dt} - u_{NN}
\]  

(5-3)

It should be pointed out that in the previous chapter the ANNC signal was added to the main signal. It was found that subtracting the NN signal gave better performance in this chapter. As discussed in Chapter 2, some researchers subtracted the NN compensation from the overall control signal. They stated that by subtracting the output of the NN compensator, the nonlinear terms would be negated. However, some papers added the NN compensation to the overall control signal.
5.3.1 ANN Inputs

According to the experiments done in the previous chapter for velocity control, it was determined that the nature of the inputs to ANN can affect performance. As a result, several experiments were conducted to investigate this issue as it relates to position control. These tests were done with 0.3 Hz sinusoid tracking (400 ± 300 mm amplitude). PID gains were already tuned for this case \( K_p = 2.25, K_i = 9 \) and \( K_d = 0.15 \).

As per Chapter 4, tracking performance was measured quantitatively with the \( RMSE \) (Root Mean Square Error). The reader is reminded that a negative \( \Delta RMSE \) means an improvement in performance (i.e. tracking error reduced).

Twelve different combinations of inputs were tested. ANNC was tuned for every single case. The tuning procedure for the ANN block was presented in Chapter 3. Figure 5-8 compares the tracking performance as measured by \( RMSE \) for different sets of inputs to the ANNC. Figure 5-9 gives the percentage improvement in performance \( \Delta RMSE \). Adding ANNC for 10 out of 12 cases is seen to reduce \( RMSE \) relative to PID. ANNC with \( P_{\text{best}} = [v \times e, \Delta P] \) as inputs shows the best performance where the \( RMSE \) drops by 25% relative to the PID controller (as highlighted by the black bar in Figure 5-8 and Figure 5-9). Except for the two cases with \( P_{\text{worst}} = [\Delta P] \) and \( P = [v \Delta P] \) as inputs, all cases show more or less the same performance (\( RMSE \) within 30 to 35 mm).

The key observation from these results is that adding more inputs to ANNC does not necessarily improve the performance. For example, ANNC with just one input (e.g. \( P_{\text{worst}} = [\Delta P] \)) is seen to give reasonable performance. It was initially believed that every available signal from the system should be used as an input to the ANNC. This is clearly not the case (i.e. more investigation needed to choose the proper inputs).
Figure 5-8 Effect on RMSE of PID+ANNC for different ANN inputs with 0.3 Hz sinusoid tracking

Figure 5-9 Effect on ΔRMSE of PID+ANNC for different ANN inputs with 0.3 Hz sinusoid tracking
5.3.2 Step Tracking

According to the previous section, the primary inputs to the ANN block should be set to $P_{\text{best}} = [v \ x \ e_x \ \Delta P]$. There are twelve secondary inputs which are created from these four primary inputs. These secondary inputs are illustrated in Figure 5-10.

In this section, the ANNC is tuned for a position setpoint with 250 mm step size at 2 s intervals. Given that PID was already tuned to its best performance (as per Section 5.2), ANNC needs to be tuned in order to show its best performance as well. The tuned parameters of the ANNC are as given in Table 5-4.

\[
\begin{align*}
\mathbf{x}(t) &= \begin{pmatrix} x(t) \\ x(t-1) \\ x(t-2) \\ x(t-3) \\ e_x(t) \\ e_x(t-1) \\ e_x(t-2) \\ v(t) \\ v(t-1) \\ v(t-2) \\ \Delta P(t) \\ \Delta P(t-1) \end{pmatrix} \\
\mathbf{u}_{NN} &
\end{align*}
\]

Figure 5-10 Input vector with twelve secondary inputs for ANNC
Figure 5-11 shows the PID+ANNC position controller result for the repeated step signal used in Section 5.2. Both the ANNC control signal \( u_{NN} \) and the overall control signal \( u \) are plotted. \( u_{NN} \) is seen to be non zero in the transient phase. As expected, \( u_{NN} \) goes to zero when the cylinder is stationary. By comparing the PID controller performance (Figure 5-3) and PID+ANNC (Figure 5-11), one sees that the addition of ANNC does not improve the response. In fact, the steady-state errors with ANNC are higher than without ANNC. However, the response is comparable, and more importantly, the ANN signal is seen to converge to zero when the cylinder is stationary.

Figure 5-12 compares the P-only, PID and PID+ANNC results. In Figure 5-13 which is the close-up of Figure 5-12, one can observe that PID has the lowest overshoot, fastest settling time and smallest steady-state error.

Figure 5-11  PID+ANNC position controller with 250 mm step size at 2 s intervals
Table 5-4 ANNC tuned parameters for the step input with 250 mm step size at 2 s intervals

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter</th>
<th>Definition</th>
<th>Default value</th>
<th>Coarse Tuning</th>
<th>Fine Tuning</th>
</tr>
</thead>
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<tr>
<td>1</td>
<td>$n_i$</td>
<td>number of inputs</td>
<td>30</td>
<td>12</td>
<td>12</td>
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<tr>
<td>2</td>
<td>$n_h$</td>
<td>number of nodes in hidden layer</td>
<td>2</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>$n_o$</td>
<td>number of outputs</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>$G$</td>
<td>learning rate of $V$</td>
<td>1</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>$F$</td>
<td>learning rate of $W$</td>
<td>1</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>$\lambda$</td>
<td>adaptation parameter</td>
<td>1</td>
<td>3</td>
<td>4.5</td>
</tr>
<tr>
<td>7</td>
<td>$s$</td>
<td>slope of sigmoid activation function</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>bias</td>
<td>activation function bias</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>$V_{lim}$</td>
<td>limit of $V$</td>
<td>$1 \times 10^7$</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>$W_{lim}$</td>
<td>limit of $W$</td>
<td>$1 \times 10^7$</td>
<td>10</td>
<td>10</td>
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<td>$K_z$</td>
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<td>0</td>
<td>0.48</td>
</tr>
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<td>$\overline{Z}$</td>
<td>tunable parameter</td>
<td>0</td>
<td>0</td>
<td>0.48</td>
</tr>
</tbody>
</table>
Figure 5-12 Comparison of P-only, PID and PID+ANNC position controller results

Figure 5-13 Close-up of Figure 5-12
5.3.3 Sinusoid Tracking

In the previous section, one observed that ANNC was unable to improve the PID response for step tracking. However, the dynamic nature of ANN could be helpful when it is applied to sinusoid tracking.

Figure 5-14 gives the PID+ANNC controller start-up response at 0.2 Hz in order to show the pressure equilibrium dynamics. One should note the slow rise in $P_a$ and $P_b$ as they reach their equilibrium values on the order of 300 kPa ± 50 kPa after two cycles.

In Figure 5-15, the weight equilibrium dynamics of ANNC are illustrated. $V$ and $W$ have 120 and 10 elements, respectively (refer to Figure 3-8). For $V$, four weights, and for $W$, two weights are selected to be shown (namely $V1$, $V41$, $V81$, $V111$ and $W1$, $W5$) in order to illustrate the different dynamics of the weights. As shown in the figure, the weights reach equilibrium within one cycle.

Figure 5-16 and Figure 5-17 illustrate the performance of the PID+ANNC controller at 0.2 Hz, with default and coarse tuned parameters for the ANNC, respectively. The coarse tuning is seen to be comparable with the fine tuning in terms of setpoint tracking and steady-state error.

One should note that Figure 5-18 to Figure 5-20 are for the system when it is in equilibrium. Thus, except for Figure 5-14 and Figure 5-15, all tests start after the cylinder has been cycled three times to ensure that the system is in equilibrium.

Extensive work was done to tune the ANN block. Although the tuning procedure for a NN is normally ad hoc, a more formal tuning procedure was presented for ANN in Chapter 3. It involved three steps: default (initialization), coarse tuning and fine tuning.

Figure 5-18, Figure 5-19 and Figure 5-20 show the PID+ANNC controller results at 0.1, 0.2 and 0.5 Hz, respectively. The ANNC control signal ($u_{NN}$) is plotted to show its contribution relative to the overall control signal ($u$). In terms of oscillation, the response for 0.1 Hz (Figure 5-18) is the worst. The error signal does not settle down. By contrast, the response at 0.5 Hz (Figure 5-20) gives the best performance in terms of a reduced level of oscillation. At higher speeds there is less friction to deal with.
Figure 5-14 PID+ANNC, system start-up to show pressure equilibrium dynamics, 0.2 Hz sinusoid tracking (500 ± 300 mm amplitude)

Figure 5-15 PID+ANNC, system start-up to show equilibrium dynamics of selected weights, 0.2 Hz sinusoid tracking (500 ± 300 mm amplitude)
Figure 5-16 PID+ANNC position controller default tuning, 0.2 Hz sinusoid tracking
(500 ± 300 mm amplitude)

Figure 5-17 PID+ANNC position controller coarse tuning, 0.2 Hz sinusoid tracking
(500 ± 300 mm amplitude)
Figure 5-18 PID+ANNC position controller, 0.1 Hz sinusoid tracking (500 ± 300 mm amplitude)

Figure 5-19 PID+ANNC position controller, 0.2 Hz sinusoid tracking (500 ± 300 mm amplitude)
5.4 Quantitative Performance Comparison

In this section, a quantitative comparison of the performance of the controllers will be given. For sinusoid tracking, the performance is given by two quantitative measures: Root Mean Square Error (RMSE) and Average Error (AVGE). The definitions for RMSE and ΔRMSE were given in Equation 4-3 and 4-4. AVGE and ΔAVGE are given by:

\[
AVGE = \frac{\sum_{i=1}^{N} |error_i|}{N} \quad \text{(5-4)}
\]

\[
\Delta AVGE_i = \frac{AVGE_i - AVGE_{ref}}{AVGE_{ref}} \times 100 \quad \text{(5-5)}
\]

where \(N\) is the number of samples and \(AVGE_{ref}\) denotes the AVGE of the reference signal. A negative ΔRMSE and a negative ΔAVGE mean an improvement in performance (i.e. tracking error reduced). For step tracking, the performance comparison is based only on average steady-state error.
5.4.1 Step Tracking

Table 5-5 provides a quantitative performance comparison based on the average of steady-state error for the step setpoint in both \( \text{mm} \) and percentage of the step size. Adding ANNC degrades the performance. It increases the average steady-state (SS) error from 4.6 \( \text{mm} \) for the PID controller to 9.7 \( \text{mm} \) with ANNC (111% worse). However, by comparing Figure 5-3 and Figure 5-11, one notes that PID+ANNC controller does a better job at the midpoint of the cycle. At this point, ANNC reduces the average SS error from 3.1 \( \text{mm} \) to 1.6 \( \text{mm} \) (48% better).

For step tracking, Kothapalli and Hassan (2008) used a NN to adjust the gains of a PI position controller for a pneumatic system. Figure 2-45 gave their PI+NN result for a square wave setpoint. The average steady-state error was about 20 \( \text{mm} \) (4% on a 500 \( \text{mm} \) step). The result for PID, given in Table 5-5, indicates better performance than Kothapalli and Hassan’s work on a percentage basis. However, the PID+ANNC performance is the same as Kothapalli and Hassan’s controller.

Again for step tracking, Ning and Bone (2002) reported success in using a model-based friction compensator along with a PVA controller for a pneumatic system. According to Figure 2-10, they could achieve an average steady-state error of 0.01 \( \text{mm} \) (0.005% on a 200 \( \text{mm} \) step) for a step input. By comparing the percentage of the step size (0.005% relative to 4%), one sees that Ning and Bone achieved remarkably better performance.

Table 5-5 Performances for the step tracking with 250 mm step size at 2 s intervals

<table>
<thead>
<tr>
<th>Intervals (s)</th>
<th>Controller Type</th>
<th>PID Average SS Error</th>
<th>PID+ANNC Average SS Error</th>
<th>Degradation (%) PID+ANNC relative to PID</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Figure No.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PID</td>
<td>% of step size</td>
<td>PID+ANNC</td>
<td>% of step size</td>
</tr>
<tr>
<td>2</td>
<td>5-3</td>
<td>4.6</td>
<td>1.8</td>
<td>5-11</td>
</tr>
<tr>
<td></td>
<td>Average SS Error</td>
<td>% of step size</td>
<td>Average SS Error</td>
<td>% of step size</td>
</tr>
<tr>
<td></td>
<td>4.6</td>
<td>1.8</td>
<td>9.7</td>
<td>3.9</td>
</tr>
</tbody>
</table>

111
5.4.2 Sinusoid Tracking

Table 5-6 gives a comparison of the performance of PID and PID+ANNC for different tracking frequencies, as measured by \( \text{RMSE} \) and \( \text{AVGE} \). Figure 5-21 provides the same results for \( \text{RMSE} \), but graphically. For all frequencies, the addition of ANNC to the PID controller is seen to improve performance, with the drop in \( \text{RMSE} \) ranging from 15% to 26%. One is reminded that the PID gains and the ANNC parameters were fixed for all test cases. Thus, it is the adaptive nature of ANNC that one attributes the ability of the PID+ANNC controller to improve performance across a range of tracking frequencies.

For sinusoid tracking, Choi et al (1998) studied feedback linearization by means of a NN toolbox for position control of a pneumatic actuator. At 0.1 \( \text{Hz} \) sinusoid tracking, they reported an average error of 0.8 \( \text{mm} \) with PID+NN which was a 67% better than PID for 0.1 \( \text{Hz} \). For a 0.2 \( \text{Hz} \) sinusoid tracking, the average error of 0.8 \( \text{mm} \) with PID+NN showed a 74% improvement in performance over PID for 0.2 \( \text{Hz} \). Finally, at 0.5 \( \text{Hz} \) sinusoid tracking, the average error of 2.2 \( \text{mm} \) with PID+NN gave a 74% better than PID for 0.5 \( \text{Hz} \). By comparing the \( \Delta \text{AVGE} \) of Choi et al with those given in Table 5-6, one observes that their results are better. However, the values are still comparable (26% in Table 5-6 and 74% for Choi et al). One should report that they did not mention whether they tuned NN individually for each case. In this thesis, the NN was tuned only for the case of the step setpoint, and then applied to sinusoid tracking.

Again for sinusoid tracking, Ning and Bone (2005) provided an experimental comparison of two pneumatic position control algorithms; PVA+feedforward+deadzone compensation (PVA+FF+DZC) and Sliding Mode Control (SMC). The tracking performances were presented as \( \text{RMSE} \). The PVA+FF+DZC controller had \( \text{RMSE} \) of 0.9 \( \text{mm} \) on a sinusoid tracking at 0.5 \( \text{Hz} \). SMC reduced the \( \text{RMSE} \) to 0.4 \( \text{mm} \) (56% improvement relative to PVA+FF+DZC). They did not compare any of these controllers with a conventional PID controller.

The reader is cautioned not to directly compare absolute \( \text{RMSE} \) values from different researchers, as the value of the \( \text{RMSE} \) depends on the length of the test and the size of the sample (as per \( N \) in Equation 5-4). However, it is appropriate to compare the \( \Delta \text{RMSE} \) as the percentage change. Thus, one notes that the percentage improvements shown by Ning and Bone and those in Table 5-6 are seen to be comparable (26% in Table 5-6 and 56% for Ning and Bone). It is important to report that Ning and Bone found that a certain level of chatter in the control signal acted as a dither signal. This reduced the problem of stick-slip friction, and consequently improved the tracking performance.
Table 5-6 Performances of PID and PID+ANNC for sinusoid tracking at different frequencies (500 ± 300 mm amplitude)

<table>
<thead>
<tr>
<th>Frequency (Hz)</th>
<th>Controller Type</th>
<th>Percentage change PID+ANNC relative to PID</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PID</td>
<td>PID+ANNC</td>
</tr>
<tr>
<td></td>
<td>Figure No.</td>
<td>AVGE (mm)</td>
</tr>
<tr>
<td>0.1</td>
<td>5-4</td>
<td>31</td>
</tr>
<tr>
<td>0.2</td>
<td>5-5</td>
<td>45</td>
</tr>
<tr>
<td>0.5</td>
<td>5-6</td>
<td>110</td>
</tr>
</tbody>
</table>

Figure 5-21 RMSE of PID and PID+ANNC for sinusoid tracking at different frequencies (500 ± 300 mm amplitude)
5.5 Summary

In this chapter, position control of the pneumatic system was examined, as applied to both step and sinusoidal tracking. Based upon the experience gained with velocity control (Chapter 4), only two controllers were examined: 1) PID and 2) PID+ANNC. The methodology and the results of the controllers were presented. The controllers were tuned for step changes in the setpoint. Their performance was evaluated as applied to sinusoid tracking. It was concluded that adding ANNC improved the tracking performance by over 20%.

Highlights from this chapter can be stated as:

- Plots of the ANNC weights illustrated rapid convergence to their equilibrium values.
- Adding more inputs to ANN did not necessarily improve the performance.
- Subtracting the ANNC signal from the overall control signal gave better performance than adding the signal.
- In step tracking, PID performance was better than PID+ANNC.
- In sinusoid tracking, PID+ANNC performance was better than PID.
Chapter 6

Conclusions and Recommendations

A position and velocity controller was designed and evaluated for a pneumatic system. An adaptive NN algorithm was implemented as both a controller and as a compensator. Performance was reported quantitatively and compared with the performance of a conventional PID controller.

6.1 Conclusions

Chapter 2 presented a literature review on six subjects: 1) pneumatic system control, 2) pneumatic control with compensation, 3) Neural Network (NN), 4) NN as a controller, 5) NN as a compensator and 6) online versus offline NN. The following can be presented as the main observations from Chapter 2:

- Considerable research has been conducted on the control of pneumatic systems due to their potential as a low-cost, clean, high power-to-weight ratio actuators. However, nonlinearities such as those due to compressibility of air continue to limit their accuracy.

- Among the nonlinearities in a pneumatic system, friction can have a significant effect on tracking performance, especially in applications that use rodless cylinders which have higher Coulomb friction than rodded cylinders.

- Compensation for nonlinearities in pneumatic systems has been a popular area of research in pneumatic system control.

- Most of the compensation strategies use model based algorithms. Although they show relatively good results, the requirement for model parameter identification has made these methods difficult to implement.

- Using NN as a non model based algorithm is a potential solution for nonlinear term compensation in pneumatic systems.

- Most of the research on pneumatic system control with compensation has been conducted for position control. Less research has been conducted for velocity control.

- The most common performance measure for step inputs is the steady-state error.
• The most common performance measures for sinusoidal inputs are Root Mean Square Error (RMSE) and Average Error (AVGE).

• Little research has been done investigating the use of NNs as direct controllers. Most of the applications of NNs are as indirect controllers or compensators.

• In the context of NN as a compensator, some researchers added the NN signal to the overall control signal and some subtracted the NN signal from the overall control signal.

• Little research has been conducted on online versus offline NN training.

The key observation from the literature review was that a NN appears to have the potential to improve the performance of a pneumatic system, as a compensator for system nonlinearities, with training conducted online to provide an adaptive feature. Previous work has been mainly simulation in nature, and there is little experimental evidence or quantitative comparison of performance with conventional control schemes. This then provides an opportunity in this thesis to study the potential experimentally.

In Chapter 4, the apparatus was used to obtain results for the case of velocity control, in order to evaluate the performance of ANN as applied to one axis of a gantry robot. Seven different controllers were tested and their performance compared: 1) P-only, 2) PI, 3) PI+ΔP, 4) ANN, 5) ANN+ΔP, 6) P-only+ANNC (ANN compensator) and 7) PI+ANNC. For ANN and ANN+ΔP, ANN was applied as a stand-alone controller. For P-only+ANNC and PI+ANNC, ANN was applied as a compensator.

Highlights from Chapter 4 can be stated as:

• ΔP adds damping to the system. Thus, ΔP can lower the degree of oscillation.
• The performance of ANN as a stand-alone controller was comparable to that of a P-only controller.
• Overall, PI showed the best performance among the controllers examined.
• The positive effect of ANNC was best seen by comparing the untuned PI result with and without ANNC.

Finally, in Chapter 5, the apparatus was used to obtain results for the case of position control, as applied to both step and sinusoidal tracking. Based upon the experience gained with velocity control (Chapter 4), only two controllers were examined: 1) PID and 2) PID+ANNC. The methodology and the results of the controllers were presented. The controllers were tuned for step changes in the setpoint. Their performance was evaluated as applied to sinusoid tracking. It was concluded that adding ANNC improved the tracking performance by over 20%.
Highlights from Chapter 5 can be stated as:

- Plots of the ANNC weights illustrated rapid convergence to their equilibrium values.
- Adding more inputs to ANN did not necessarily improve the performance.
- Subtracting the ANNC signal from the overall control signal gave better performance than adding the signal.
- In step tracking, PID performance was better than PID+ANNC.
- In sinusoid tracking, PID+ANNC performance was better than PID.

The objective of this thesis was to design and evaluate a position and velocity controller for one axis of a pneumatic gantry robot. This was accomplished. It was shown that the addition of ANN as a compensator could improve the performance for both position and velocity control. Although performance was better than with conventional PID control, it is concluded that the degree of improvement with ANNC does not warrant the extra effort in tuning and implementation.

The original premise for ANNC is that it would be self-tuning due to its adaptive nature. This is now judged to be misleading because of the extensive setup tuning that was required, as documented in Section 3.3.2.

### 6.2 Recommendations

The following are recommendations for further work in this area:

- It was noted in Chapter 5 that ANNC had to be subtracted from the control signal, and performance was degraded if it was added. This observation needs to be examined further. Theoretically, it shouldn't matter, as ANNC should adapt itself to the correct sign. The fact that this is not the case leads to the suspicion that there is an inadvertent sign bias in the algorithm. A simulation study should be able to determine the source of this apparent anomaly.

- The ANN was based on Modified Back Propagation Network (MBPN) algorithm. One should investigate alternate algorithms such as Multilayer NNs (MNNs).

- In this thesis, a conventional PID controller was used with a NN compensator. Using a more sophisticated controller such as Sliding Mode Control (SMC) with NN compensation might produce better results.

- Only velocity and position control of a single axis (x-axis) was investigated. The work with ANN should be extended to include force control and the second axis (z-axis).
References


Appendix A

Technical Specifications

A.1 ESTO Proportional Flow Control (PFC) valve

Data sheet - Proportional directional control valve MPYE-5-M5-010-B - 154200

<table>
<thead>
<tr>
<th>Feature</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal size</td>
<td>2 mm</td>
</tr>
<tr>
<td>Type of actuation</td>
<td>Electrical</td>
</tr>
<tr>
<td>Sealing principle</td>
<td>Hard</td>
</tr>
<tr>
<td>Assembly position</td>
<td>Any</td>
</tr>
<tr>
<td>Design structure</td>
<td>Piston slide</td>
</tr>
<tr>
<td>Type of reset</td>
<td>Magnetic spring</td>
</tr>
<tr>
<td>Safety instructions</td>
<td>MPYE safety position: If the power supply cable is interrupted, travel occurs to the closed mid-position</td>
</tr>
<tr>
<td>Type of piloting</td>
<td>Direct</td>
</tr>
<tr>
<td>Flow direction</td>
<td>Non reversible</td>
</tr>
<tr>
<td>Valve function</td>
<td>5/3 closed</td>
</tr>
<tr>
<td>Polarity protected</td>
<td>For all electrical connections</td>
</tr>
<tr>
<td>Operating pressure</td>
<td>0 - 10 bar</td>
</tr>
<tr>
<td>b value</td>
<td>0.21</td>
</tr>
<tr>
<td>C value</td>
<td>0.45 l/bar</td>
</tr>
<tr>
<td>Standard nominal flow rate</td>
<td>100 l/min</td>
</tr>
<tr>
<td>Max. hysteresis</td>
<td>0.4 %</td>
</tr>
<tr>
<td>Operating voltage range DC</td>
<td>17 - 30 V</td>
</tr>
<tr>
<td>Residual ripple</td>
<td>5 %</td>
</tr>
<tr>
<td>SETPOINT/ACTUAL values</td>
<td>Voltage type 0 - 10 V</td>
</tr>
<tr>
<td>Operating medium</td>
<td>Filtered, unlubricated compressed air, 5 µm filtration</td>
</tr>
<tr>
<td>CE mark (see declaration of conformity)</td>
<td>To EU directive for EMC</td>
</tr>
<tr>
<td>Corrosion resistance classification CRC</td>
<td>2</td>
</tr>
<tr>
<td>Medium temperature</td>
<td>5 - 60 °C</td>
</tr>
<tr>
<td>Protection class</td>
<td>IP65</td>
</tr>
<tr>
<td>Ambient temperature</td>
<td>0 - 50 °C</td>
</tr>
<tr>
<td>Authorisation</td>
<td>C-Tick</td>
</tr>
<tr>
<td>Product weight</td>
<td>290 g</td>
</tr>
</tbody>
</table>

Figure A-1 Technical specifications of FESTO PFC valve (www.festo.com)
A.2 SMC MY1H Cylinder

Mechanically Jointed Rodless Cylinder
High Precision Guide Type
Series MY1H

Specifications

<table>
<thead>
<tr>
<th>Zone size (cm)</th>
<th>10</th>
<th>16</th>
<th>20</th>
<th>25</th>
<th>32</th>
<th>40</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pole</td>
<td>AV</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Action</td>
<td>Double-acting</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating pressure range (kPa)</td>
<td>0.4 to 6.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proof pressure</td>
<td>1.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ambient air temperature</td>
<td>0 to 50 °C</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cylinder</td>
<td>0 to 50 °C</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lubrication</td>
<td>NBRnub</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Stroke length (inches) 1.8

Piping port

Stroke adjusting unit specifications

<table>
<thead>
<tr>
<th>Unit size (mm)</th>
<th>10</th>
<th>16</th>
<th>20</th>
<th>25</th>
<th>32</th>
<th>40</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit symbol</td>
<td>H</td>
<td>A</td>
<td>L</td>
<td>A</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>Extension stroke (mm)</td>
<td>0 to 10</td>
<td>0 to 5.6</td>
<td>0 to 6</td>
<td>0 to 11.6</td>
<td>0 to 12</td>
<td>0 to 18</td>
</tr>
<tr>
<td>Stroke adjustment range</td>
<td>When exceeding the stroke limit adjustment range, utilize a made-to-order specification &quot;X415&quot; and &quot;X417&quot;.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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Shock Absorber Specifications

<table>
<thead>
<tr>
<th>Model</th>
<th>RD 0905</th>
<th>RD 0906</th>
<th>RD 1007</th>
<th>RD 1412</th>
<th>RD 2015</th>
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<tbody>
<tr>
<td>Min. energy absorption (J)</td>
<td>1.0</td>
<td>2.4</td>
<td>5.9</td>
<td>13.6</td>
<td>25.8</td>
</tr>
<tr>
<td>Stroke absorption (mm)</td>
<td>5</td>
<td>0</td>
<td>7</td>
<td>12</td>
<td>15</td>
</tr>
<tr>
<td>Max. oil leakage (ml/min)</td>
<td>5.5</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
</tr>
<tr>
<td>Max. oil consumption (ml/min)</td>
<td>65</td>
<td>60</td>
<td>70</td>
<td>45</td>
<td>25</td>
</tr>
<tr>
<td>Spring force (N)</td>
<td>Extended 196</td>
<td>1.6</td>
<td>4.22</td>
<td>6.68</td>
<td>9.06</td>
</tr>
<tr>
<td>Reclined</td>
<td>9.00</td>
<td>4.22</td>
<td>6.68</td>
<td>9.06</td>
<td>9.06</td>
</tr>
<tr>
<td>Opening (max. angular) (°)</td>
<td>5 to 80</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Piston Speed

<table>
<thead>
<tr>
<th>Stroke size (mm)</th>
<th>10</th>
<th>16 to 40</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stroke adjusting unit</td>
<td>100 to 300</td>
<td>100 to 1000</td>
</tr>
<tr>
<td>L and H unit</td>
<td>100 to 1000</td>
<td>100 to 1000</td>
</tr>
</tbody>
</table>

Note 1: Be aware that when the stroke adjusting range is increased by manipulating the adjusting bolt, the air outflow capacity decreases. Also, when exceeding the air outflow stroke ranges on page 6-11/77, the piston speed should be 100 to 200 mm per second.

Note 2: Use at a speed within the absorption capacity range. Refer to page 6-11/77.

Standard Stroke

<table>
<thead>
<tr>
<th>Stroke size</th>
<th>Standard stroke (mm)</th>
<th>Maximum stroke (mm) (±0.3) (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.16, 20</td>
<td>100, 150, 200, 300</td>
<td>200, 200, 200, 200</td>
</tr>
<tr>
<td>25, 32, 40</td>
<td>150</td>
<td>300</td>
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</tbody>
</table>

Lock Specifications

<table>
<thead>
<tr>
<th>Stroke size (mm)</th>
<th>10</th>
<th>16 to 40</th>
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</thead>
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<tr>
<td>Lock position</td>
<td>One end (selectable), both ends</td>
<td></td>
</tr>
<tr>
<td>Holding force (Max.) (N)</td>
<td>110</td>
<td>170</td>
</tr>
<tr>
<td>Reclined stroke adjusting range (mm)</td>
<td>0 to 5.6</td>
<td>0 to 6</td>
</tr>
<tr>
<td>Bore size</td>
<td>1 mm or less</td>
<td></td>
</tr>
<tr>
<td>Manual release</td>
<td>Possible (Not lock type)</td>
<td></td>
</tr>
</tbody>
</table>

Made to Order Specifications
(For details, refer to page 8-31-1)

Symbol Specifications

-<B016> Intermediate stroke (Using exclusive body)
-<B017> Long stroke
-<B018> NPT finish piping hole
-<B056> With knock pin hole
-<B097> NBR valve fitting in dust seal band
-<B18> Vertical insert thread specifications
-<B18> Holder mounting bracket T
-<B17> Holder mounting bracket T

Figure A-2 Technical specifications of SMC MY1H cylinder (www.smcworld.com)
A.3 Celesto Position and Velocity Transducer

Position and Velocity Output Signals
Ranges: 0-2 to 0-100 inches
Instrument Grade

<table>
<thead>
<tr>
<th>Specification Summary:</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GENERAL</strong></td>
</tr>
<tr>
<td>Full Stroke Range Options ..................................... 0-2 to 0-100 inches</td>
</tr>
<tr>
<td>Measuring Cable ................................................. see ordering information</td>
</tr>
<tr>
<td>Enclosure Material ............................................. powder-painted and anodized aluminum</td>
</tr>
<tr>
<td>Weight ............................................................. 2 lbs. max</td>
</tr>
</tbody>
</table>

| **POSITION**           |
| Output Signal ................. voltage divider (potentiometer) |
| Accuracy ...................... ±0.25% to ±0.10% full stroke see ordering information |
| Repeatability ................ ±0.02% full stroke |
| Resolution .................... essentially infinite |
| Sensor .......................... plastic-hybrid precision potentiometer |
| Input Resistance Options .......... 500, 1k, 5k or 10kΩ see ordering information |
| Power Rating, Watts .............. 2 watts at 70°F derated to 0°F 250°F |
| Maximum Input Voltage ............ see ordering information |
| Output Signal Change Over Full Stroke Range .......... ±4% ±4% of input voltage |

| **VELOCITY**            |
| Output Signal ................. DC tachometer output |
| Linearity ..................................... better than ±0.01% of output at any velocity |
| Repeatability ................ ±0.01% of reading |
| Maximum Velocity - Retraction Acceleration .......... see ordering information |
| Sensor .......................... tach generator |
| Input Voltage ....................... none required |
| Output Voltage @ 100 inches per minute .......... see ordering information |
| Output Ripple (when output ≥ 280 mV) .............. ±3% rms |

| **ENVIRONMENTAL**       |
| Enclosure ...................... NEMA 1 |
| Operating Temperature .......... -40°F to 200°F (-40°C to 90°C) |
| Vibration ....................... up to 10 g @ 2 to 2000 Hz maximum |

The DV301 is a combination position and velocity transducer for full-scale measurement ranges from 0 to 100 inches. A precision plastic-hybrid potentiometer provides accurate position feedback while a self-generating DC tachometer provides a velocity signal that is proportional to the speed of the traveling stainless-steel measuring cable.

Output Signals

```
Position     Velocity
```

Figure A-3 Technical specifications of Celesto cable extension transducer (www.clesto.com)
A.4 Omega Differential Pressure Sensor

LOW-COST SILICON PRESSURE SENSOR WITH MILLIVOLT OUTPUT

PX137 Series
0-0.3 to 0-100 psi
0-0.62 to 0-6.9 bar

Available for Differential, Gage, or Absolute Measurement
Calibrated Millivolt Output
Precise Temperature Compensation

The PX137 Series pressure transducers use state-of-the-art micro-machined silicon pressure sensors in conjunction with stress-free packaging techniques to provide highly accurate, temperature-compensated pressure measurements for the most demanding applications.

SPECIFICATIONS
Excitation Voltage: 12 Vdc (10 max)
Linearity and Hysteresis: ±0.1% FS typical, ±0.2% max (0.01% for 0.5 psi range)
Repeatability: ±0.05% FS typical, ±0.1% FS max
Zero Balance: ±1 mV (±3 mV for 0.3 psi range)
Input Resistance: 10 kΩ

Dimensions: mm (in)

Storage Temp: -40 to 125°C
(-40 to 257°F)
Operating Temp: 0 to 70°C
(32 to 158°F)
Span Temp Effects:
±1.0% FS 0 to 50°C (32 to 122°F)
±0.5% FS 50 to 70°C (122 to 158°F)
Zero Temp Effects:
±0.05% FS 0 to 50°C (32 to 122°F)
±0.2% FS 50 to 70°C (122 to 158°F)
For 0.3 psi Range:
±1.0 mV 0 to 50°C (32 to 122°F)
±0.5 mV 50 to 70°C (122 to 158°F)
Proof Pressure: >3x FS pressure
Burst Pressure: >5x FS pressure
Common-Mode Pressure: 50 psi
Flux Exclusion: For use with gases compatible with silicon, glass-featured nylon and alumina ceramic

ALL MODELS AVAILABLE FOR FAST DELIVERY!

To Order (Specify Model Number)

<table>
<thead>
<tr>
<th>GAGE DIFFERENTIAL PRESSURE RANGES</th>
<th>MODEL NO.</th>
<th>PRICE</th>
<th>FS OUTPUT (0-12 V EXC)</th>
<th>COMPATIBLE METERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>±0.3 psi (8.3 in H₂O) 0.02 bar (2 kPa)</td>
<td>PX137-0.3DV</td>
<td>$105</td>
<td>18 ±2 mV</td>
<td>DP25B-S, DP41S</td>
</tr>
<tr>
<td>±1 psi</td>
<td>PX137-0.01DV</td>
<td>55</td>
<td>18 ±1 mV</td>
<td>DP25B-S, DP41S</td>
</tr>
<tr>
<td>±5 psi</td>
<td>PX137-005DV</td>
<td>55</td>
<td>60 ±2.5 mV</td>
<td>DP25B-S, DP41S</td>
</tr>
<tr>
<td>±15 psi</td>
<td>PX137-015DV</td>
<td>55</td>
<td>90 ±5 mV</td>
<td>DP25B-S, DP41S</td>
</tr>
<tr>
<td>±30 psi</td>
<td>PX137-030DV</td>
<td>55</td>
<td>90 ±5 mV</td>
<td>DP25B-S, DP41S</td>
</tr>
<tr>
<td>±100 psi</td>
<td>PX137-100DV</td>
<td>55</td>
<td>100 ±5 mV</td>
<td>DP25B-S, DP41S</td>
</tr>
<tr>
<td>ABSOLUTE PRESSURE RANGES</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>±1 psi</td>
<td>PX137-015AV</td>
<td>$95</td>
<td>90 ±5 mV</td>
<td>DP25B-S, DP41S</td>
</tr>
</tbody>
</table>

ORDERING EXAMPLE: PX137-015AV, n If using gasses, order absolute pressure sensor with 0 to 15 psi absolute pressure range. $95.

ACCESSORY

<table>
<thead>
<tr>
<th>MODEL NO.</th>
<th>PRICE</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>CM-4355</td>
<td>$80</td>
<td>Reference Book: Automated Continuous Process Control</td>
</tr>
</tbody>
</table>

Figure A-4 Technical specifications of Omega PX137 (www.omega.com)
A.5 DMD-465WB Signal Conditioner

**STRAIN AMPLIFIER/SIGNAL CONDITIONER MODULES FOR STRAIN GAGES, LOAD CELLS, AND TRANSDUCERS**

**DMD-460 Series**

- Bridge Excitation: 4 to 15 Vdc Up to 120 mA
- Works with 120, 350, 500 Ω, and Greater Bridge Circuits
- Adjustable Gain and Offset
- 6-Wire Bridge Connections
- Voltage and Current Output Versions
- 115 and 230 Vac, and DC-Powered Models.

The DMD-460 Series bridge amplifiers are self-contained AC- or DC-powered, signal conditioning modules for strain gages, load cells, and bridge-type sensors. The DMD-465 contains a precision differential instrumentation amplifier with voltage output. The similar DMD-465WB has a frequency response to 2 kHz, while the DMD-466 has a 4 to 20 mA output instead of a voltage output.

**SPECIFICATIONS**

**COMMON**
- Power: Standard 115 Vac or optional 220 Vac ±10% 50/60 Hz or 11 to 36 Vac 0.7 A @ 0 V, 0.17 A @ 36 V at maximum excitation load
- Operating Temperature: 0 to 70°C (32 to 158°F)
- Storage Temperature: -25 to 55°C (-13 to 131°F)
- Weight: 0.10 g (0.03 oz)
- Size: 96 L x 51 W x 33 mm H (3.75 x 2 x 1.3″)

**BRIDGE SUPPLY**
- Excitation Voltage Range: 4 to 15 Vdc
- Current Output: 120 mA max
- Line and Load Regulation: ±0.02% (100 ma) ±0.05% max
- Output Noise: 0.5 mVrms

**VOLTAGE OUTPUT**
- DMD-465 and DMD-465WB
- Gain Range: 40 to 250 (up to 1000 with external resistor on DMD-465 only)

**Dynamic Response:**
- DMD-465: DC to -3 dB = 3 Hz
- DMD-465WB: DC to -3 dB = 2 Hz
- Max Output (± 10 V Load): ±10 Vdc
- Output Impedance: 3.01 ± 1 Ω
- Output Offset: ±5 to 2 V
- DMD-465WB only:
  - Gain Temp Coefficient: 200 ppm/°C
  - Input Impedance: 30 kΩ
  - Input Impedance: 2000 MΩ
- Output Noise (RMS): @ gain = 100
  - DMD-465: 120 µVrms
  - DMD-465WB: 1 to 2 kHz = 2 mV
  - Input Noise Line Frequency: ±15 µVpp
- Common-Mode Rejection: 90 dB @ gain = 10, 100 dB @ gain = 200
- Common-Mode Input Voltage: ±15 V

**To Order (Specify Model Number)**

<table>
<thead>
<tr>
<th>MODEL NO.</th>
<th>PRICE</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>DMD-465</td>
<td>3350</td>
<td>Voltage output</td>
</tr>
<tr>
<td>DMD-465-220V</td>
<td>350</td>
<td>220 Vac powered DMD-465</td>
</tr>
<tr>
<td>DMD-465WB</td>
<td>350</td>
<td>High-frequency voltage output</td>
</tr>
<tr>
<td>DMD-465WB-220V</td>
<td>350</td>
<td>220 Vac powered DMD-465WB</td>
</tr>
<tr>
<td>DMD-466</td>
<td>350</td>
<td>Current output (4 to 20 mA)</td>
</tr>
<tr>
<td>DMD-466-220V</td>
<td>350</td>
<td>220 Vac powered DMD-466</td>
</tr>
<tr>
<td>DMD-466-DC</td>
<td>350</td>
<td>10 to 36 Vac powered DMD-466</td>
</tr>
</tbody>
</table>

*Most Popular Models Highlighted*

**ACCESSORY**

<table>
<thead>
<tr>
<th>MODEL NO.</th>
<th>Price</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>EE-2454</td>
<td>$160</td>
<td>Reference Book: The Industrial Electronics Handbook</td>
</tr>
</tbody>
</table>

Figure A-5 Technical specifications of Omega DMD-460WB amplifier (www.omega.com)
# A.6 dSPACE DS1104 R&D Controller Board

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processor</td>
<td>• MPC8240 processor with PPC 603e core and on-chip peripherals&lt;br&gt; • 64-bit floating-point processor&lt;br&gt; • CPU clock: 250 MHz&lt;br&gt; • 2 x 16 KB cache, on-chip&lt;br&gt; • On-chip PCI bridge (33 MHz)</td>
</tr>
<tr>
<td>Memory</td>
<td><strong>Global memory</strong>&lt;br&gt; 32 MB DRAM&lt;br&gt; <strong>Flash memory</strong>&lt;br&gt; 8 MB</td>
</tr>
<tr>
<td>Timer</td>
<td>4 general-purpose timers&lt;br&gt; • 32-bit down counter&lt;br&gt; • Reload by hardware&lt;br&gt; • 80-ns resolution&lt;br&gt; 1 sampling rate timer (decrementer)&lt;br&gt; • 32-bit down counter&lt;br&gt; • Reload by software&lt;br&gt; • 40-ns resolution&lt;br&gt; 1 time base counter&lt;br&gt; • 64-bit up counter&lt;br&gt; • 40-ns resolution</td>
</tr>
<tr>
<td>Interrupt controller</td>
<td>• 5 timer interrupts&lt;br&gt; • 2 incremental encoder index line interrupts&lt;br&gt; • 1 UART interrupt&lt;br&gt; • 1 slave DSP interrupt&lt;br&gt; • 1 slave DSP PWM interrupt&lt;br&gt; • 5 A/D converter channel (selectable conversion) interrupts&lt;br&gt; • 1 host interrupt&lt;br&gt; • 4 external interrupts (user interrupts)</td>
</tr>
<tr>
<td>A/D converter</td>
<td><strong>Channels</strong>&lt;br&gt; 4 multiplexed channels equipped with one sample &amp; hold A/D converter (1x16-bit)&lt;br&gt; 4 parallel channels equipped with one sample &amp; hold A/D converter (4x12-bit)&lt;br&gt; Note: 5 A/D converter channels (1x16-bit and 4x12-bit) can be sampled simultaneously&lt;br&gt; <strong>Resolution</strong>&lt;br&gt; • Multiplexed channels: 16 bit&lt;br&gt; • Parallel channels: 12 bit&lt;br&gt; <strong>Input voltage range</strong>&lt;br&gt; ±10 V&lt;br&gt; <strong>Conversion time</strong>&lt;br&gt; • Multiplexed channels: 2 μs&lt;sup&gt;1&lt;/sup&gt;&lt;br&gt; • Parallel channels: 300 ns&lt;sup&gt;1&lt;/sup&gt;&lt;br&gt; <strong>Offset error</strong>&lt;br&gt; ±5 mV&lt;br&gt; <strong>Gain error</strong>&lt;br&gt; • Multiplexed channels: ±0.25%&lt;br&gt; • Parallel channels: ±0.5%&lt;br&gt; <strong>Offset drift</strong>&lt;br&gt; ±4 ppmK&lt;br&gt; <strong>Gain drift</strong>&lt;br&gt; ±25 ppmK&lt;br&gt; <strong>Signal-to-noise ratio</strong>&lt;br&gt; • Multiplexed channels: &gt;80 dB&lt;br&gt; • Parallel channels: &gt;65 dB</td>
</tr>
<tr>
<td>D/A converter</td>
<td><strong>Channels</strong>&lt;br&gt; 2 channels&lt;br&gt; <strong>Resolution</strong>&lt;br&gt; 16-bit&lt;br&gt; <strong>Output range</strong>&lt;br&gt; ±10 V&lt;br&gt; <strong>Settling time</strong>&lt;br&gt; Max. 10 μs (full-scale, accuracy 1% LSB)&lt;br&gt; <strong>Offset error</strong>&lt;br&gt; ±1 mV&lt;br&gt; <strong>Gain error</strong>&lt;br&gt; ±0.1%&lt;br&gt; <strong>Offset drift</strong>&lt;br&gt; ±13 ppmK&lt;br&gt; <strong>Gain drift</strong>&lt;br&gt; ±25 ppmK&lt;br&gt; <strong>Signal-to-noise ratio</strong>&lt;br&gt; &gt;80 dB&lt;br&gt; <strong>I&lt;sub&gt;IN&lt;/sub&gt;</strong>&lt;br&gt; ±5 mA</td>
</tr>
<tr>
<td>Digital I/O</td>
<td><strong>Channels</strong>&lt;br&gt; 20-bit parallel I/O&lt;br&gt; Single bit selectable for input or output&lt;br&gt; <strong>Voltage range</strong>&lt;br&gt; TTL input/output levels&lt;br&gt; <strong>I&lt;sub&gt;IN&lt;/sub&gt;</strong>&lt;br&gt; ±5 mA</td>
</tr>
</tbody>
</table>

---

*<sup>1</sup> Speck and timing specifications subject to the capabilities of the hardware components and circuits of our products. Depending on the software configuration, the attainable overall performance figures can deviate significantly from the hardware specifications.*

---

Figure A-6 Technical specification of dSPACE DS1104 R&D controller board

([www.dspace.de/ww/en/pub/start.cfm](http://www.dspace.de/ww/en/pub/start.cfm))
A.7 SMC Mist Separator

Mist Separator Series (N)AM

- Part Sizes ⅛,⅜,¼,⅛,⅛
- Removes 99.9% of Oil Mist and Fine Particles down to 0.3μm
- Manual or Automatic Drain
- Cartridge Type Element for easy replacement
- Small additional clearance required for cartridge replacement

Mist Separators are also available for the
Modular Range of Air Preparation Products

Figure A-7 Technical specifications of SMC mist separator (www.smcworld.com)
A.8 SMC Filter Regulator

Figure A-8 Technical specifications of SMC directional flow valve (www.smcworld.com)
A.9 FESTO Air Reservoir

Figure A-9 Technical specifications of FESTO air reservoir (www.festo.com)
Appendix B

Noise in Signals

This appendix gives a quantitative parameter for measuring the level of noise in the signals. At the end of this part we introduce the first order filter that we have used and its tuning procedure.

B.1 Noise in Measured Signals

The performance of any control systems depends on the level of electrical noise in the system. The overall noise level depends on the quality of the sensors, amplifiers and controller board. To obtain a measure of the noise level in the system the sensors need to be calibrated at first.

It should be remarked that this measurement executed under the condition in which all the devices connected to the apparatus were functioning. That is to say, the cylinders $x$ and $z$ were kept still in the mid-position which is considered their most frequent working positions, so, we are guaranteed that we will have the maximum amount of noise.

Table B-1 indicates the noise levels for the measured signals in terms of the maximum Signal to Noise Ratio (SNR) which was calculated as defined in Storey (1998):

$$\text{maximum SNR} = 20 \log_{10}\left(\frac{\text{maximum}}{\text{RMS of noise}}\right)$$  \hspace{1cm} (B-1)

where RMS is the Root Mean Square. An acceptable minimum SNR is between 2 and 3 dB (Storey, 1998 pp.85 and 338). As the maximum SNR levels were all above 3 dB the conclusion was that no active filtering was required. RMS is measured by means of scaled data, meaning, the mean value of the signals have been deducted from the raw values.

$$RMS = \sqrt{\frac{\sum(nsignal - signal_{mean})^2}{n}}$$  \hspace{1cm} (B-2)

Where $n$ is the number of data. As it can be seen from Figure B-1 and Figure B-2; the raw data have been plotted for two different time intervals.

Furthermore, for the maximum signal we have $x=1007$ mm and for $z=94$ mm. That is interesting; because the maximum strokes of the cylinders are 1007 and 100 mm. However, the point is, this max value can be measured depends on different data. This is to say:
That is the reason we have 1007 mm for the \( x \) value and 94 for the \( z \) max value. By the way, to be conservative, we can pick 1007 for \( x \) and 100 for \( z \). In fact, we are in the safe side, so it does not really matter which value we are going to be set for the \( x \) and \( z \) max value.

Also, for velocity signals we kept the system “ON”; meaning the cylinder was been held still at the mid position. This table basically shows that we can face much more amount of noise if we wait a bit longer.

Table B-1 Signal to Noise Ratio

<table>
<thead>
<tr>
<th>No.</th>
<th>Signal</th>
<th>Time (s)</th>
<th>( n )</th>
<th>Maximum Signal</th>
<th>RMS of noise</th>
<th>Maximum SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( x )</td>
<td>100</td>
<td>10001</td>
<td>1007 mm</td>
<td>0.3441</td>
<td>69</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10</td>
<td>1001</td>
<td>1007 mm</td>
<td>0.2892</td>
<td>71</td>
</tr>
<tr>
<td>2</td>
<td>( z )</td>
<td>100</td>
<td>10001</td>
<td>100 mm</td>
<td>0.1169</td>
<td>58</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10</td>
<td>1001</td>
<td>100 mm</td>
<td>0.1148</td>
<td>58</td>
</tr>
<tr>
<td>3</td>
<td>( V_x )</td>
<td>100</td>
<td>10001</td>
<td>1600 mm/sec</td>
<td>3.6938</td>
<td>53</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10</td>
<td>1001</td>
<td>1600 mm/sec</td>
<td>3.4683</td>
<td>53</td>
</tr>
<tr>
<td>4</td>
<td>( V_z )</td>
<td>100</td>
<td>10001</td>
<td>1000 mm/sec</td>
<td>0.4294</td>
<td>67</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10</td>
<td>1001</td>
<td>1000 mm/sec</td>
<td>0.4528</td>
<td>67</td>
</tr>
</tbody>
</table>
Figure B-1 x and z raw signals in 100 s

Figure B-2 x and z raw signals in 10 s
In Figure B-3 and Figure B-4 we have provided a full scale of the earlier plots. As it can be seen, the amounts of error in these two figures are quite negligible.

Concerning the noise level in the velocity signal, raw data are shown in Figure B-5 and Figure B-6 in two different time intervals. Also the full scale of the figure are illustrated in Figure B-7 and Figure B-8.

We argued that if the maximum SNR of the signal was greater than $3 \, dB$ we would be able to ignore the noise. To verify this fact, we have applied simulated noise signals to a flat line with the value as the mean of $x$ value in order to mimic the behavior. The results are shown in Figure B-9 and Figure B-10.

In order to have a feel about the signals which are noisier than the current ones, a simulated noisy signal has been generated. As it can be seen from Figure B-9 and Figure B-10, three noisy signals have been plotted. They have maxSNR of 10, 30, 60 $dB$. In Figure B-10 one is able to observe the behavior of a noisy signal which has maxSNR of 60 $dB$ in the working range. This signal is quite cleaner than the two others. In fact, since our $x$ and $z$ have higher maxSNR, they are considered as clean signals which do not need to be filtered.
Figure B-4 Full scale x and z raw data in 10 s

Figure B-5 Vx and Vz raw data in 100 s
Figure B-6 Vx and Vz raw data in 10 s

Figure B-7 Full Scale Vx and Vz raw data in 100
Figure B-8 Full Scale Vx and Vz raw data in 10 s

Figure B-9 Different “MaxSNR”s for a simulated signal
B.2 First Order Filter Design

Although in the previous topic we argued that the raw signals are not very noisy due to the quantitative measure that we introduced, we observed that we added derivative gains to the controllers it amplified the noises. In Figure B-11 we have illustrated the amount of noise that we were dealing with which is very harmful for the spool of the valves. However, the interesting part of the figure is the smooth position tracking done by the cylinder. This happens because of the extensive amount of noises which actually put the valve in a dynamic condition. This behavior leads us to end up with dynamic friction rather than static friction in the valves which the former is much less than the later. In fact, this performance could be achieved at the cost of putting the valves in a harmful situation.

Figure B-10 Full scale of Figure B-9 which is in the working range
All said, we have added a first order filter in the control loop. Tuning of the filter is done with sinusoidal input at 2 rad/s. The filter can be modeled as:

\[
\frac{1}{\tau s + 1}
\]  \hspace{1cm} (B-3)

We tried three different cut-off frequencies and based on the level of noise reduction we selected the tuned one. 2, 3 and 160 Hz were the cut-off frequencies that we tried. Based on the figures below, we chose 3Hz as the tuned filter because it can attenuate the noises when we have added the derivative action. In contrast, 160 Hz fails to attenuate the noises and also 2 Hz is considered too low for this task.

The arithmetic calculation for the time constant (\( \tau \)) and the respective cut-off frequency is as follows:

\[
\omega = 2\pi f
\]  \hspace{1cm} (B-4)
where \( \omega \) is the frequency in rad/s and \( f \) in Hz. Also we have equation B-3 which related the frequency with the time constant:

\[
\omega \approx \frac{1}{\tau}
\]  

(B-5)

where \( \tau \) is the time constant in s. By combining B-4 and B-5 we can have \( \tau \) as a function of frequency in Hz.

Table B-2 shows the respective cut-off frequencies and the time constant \( \tau \).

<table>
<thead>
<tr>
<th>Time Constant ( \tau ) (s)</th>
<th>Cut-off Frequency (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>2</td>
</tr>
<tr>
<td>0.05</td>
<td>3</td>
</tr>
<tr>
<td>0.001</td>
<td>160</td>
</tr>
</tbody>
</table>

Figure B-12  Tuned PI (Kp= 2.25 Ki=9) X-Position control, filtered \( f_c \approx 160\)Hz, 2 rad/s
Figure B-13 Tuned PI (Kp= 2.25 Ki=9) X-Position control, filtered $f_c \approx$3Hz Tuned, 2 rad/s

Figure B-14 Tuned PI (Kp= 2.25 Ki=9) X-Position control, filtered $f_c \approx$2Hz, 2 rad/s
Appendix C

z-axis Calibration

This appendix covers the calibration procedure of differential pressure and position sensors for z-axis.

C.1 Position Sensor

The calibration of the position sensors was done by moving the piston z-axis cylinder to known positions and then recording the output voltage. Figure C-1 shows the curve fitting results for the z-axis. It was found that the piston position can be calculated as follows:

\[ z = 36.72 \cdot r - 25.2 \]  \hspace{1cm} (C-1)

where \( r \) is the sensor reading in volt with \( R \approx 1 \) for the figure.

![Figure C-1 Curve fitting for the z-axis position sensor calibration data](image)
C.2 Pressure Sensor

To calibrate the differential sensors one end of the sensor was left open to atmospheric pressure while the other end was connected to the measured pressure air line. The pressure was stepped up gradually and the sensor output voltage was recorded at each pressure step. The same sequence was repeated but this time by connecting the measured pressure supply line to the sensor port that was initially left open to atmospheric pressure. Figure C-2 shows the curve fitting results for the z-axis. It was found that the differential pressure can be calculated as follows:

$$\Delta P_z = 64.79 \cdot r - 2.36$$ (C-2)

where $r$ is the sensor reading in $\text{V}_\text{out}$ with $R \approx 1$ for the figure.