DESIGN AND DEVELOPMENT OF A PROCESS CONTROL VALVE DIAGNOSTIC SYSTEM BASED ON ARTIFICIAL NEURAL NETWORK ENSEMBLES

by

SUGITH SEWDASS

Student Number: 20150121

A thesis submitted in fulfilment of the requirements for the
Master of Engineering Degree
in the
Faculty of Engineering and the Built Environment
Department of Electronic Engineering
Durban University of Technology

I undertake that all material presented in this thesis is my own work and has not been written for me, in whole or in part by any other person. I undertake that any quotation or paraphrase from the published or unpublished work of another person has been duly acknowledged in the work which I now present for examination.

Sugith Sewdass

Approved for Final Submission

Supervisor: Dr. Poobalan Govender

Durban, 06 February 2016

ACKNOWLEDGEMENTS

I would like to thank my research supervisor Dr Poobalan Govender for all his support and guidance through this research. Thank you to the National Research Foundation for their financial support, and to the Optimisation and Energy Studies Unit at the Durban University of Technology for use of the post graduate control systems laboratory.

I would also like to thank Mr Trevor Pillay, Mr Nivash Rupnarain and Mr Ray Ebrahim for their assistance.

DEDICATION

This thesis is dedicated to my Mum and Dad for their never- ending support, love and patience in all my endeavours.

ABSTRACT

This research discusses the design and development of a computational intelligent based diagnostic system to assess the operating state of a process control valve. Process control valves react to a controller signal and are the main source of faults in a control loop. The elasticity inherent within a valve's mechanical construction makes it prone to nonlinearities such as backlash, hysteresis and stiction. These nonlinearities negatively affect the performance of a process control loop during a control session.

The diagnostic system proposed in this research utilises artificial neural network systems configured as ensembles to classify common control valve faults. Each ensemble functions as a 'specialist' trained to identify a specific loop fault. The team of specialized artificial neural networks are configured into a single comprehensive system to detect common control loops problems such as valve hysteresis, backlash, stiction and low air supply. The detection of a specific type of fault is achieved by comparing the mean square error output from each network. The ensemble having the lowest mean square error is the network that has been trained to identify a specific type of fault.

Two practical methods to simulate control valve stiction and hysteresis are also presented in this study. These methods make it possible for researchers to investigate dynamics of nonlinear behaviour when these nonlinear effects occur in the control channel.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

AI: Artificial Intelligence

ANN: Artificial Neural Network

CI: Computational Intelligence

CO: Controller output

FCE: Final control element

HART: Highway addressable remote transducer

G-N: Gauss-Newton

PROFIBUS: Process field Bus

LM: Levenberg-Marquardt

MV: Measured variable

PV: Process variable

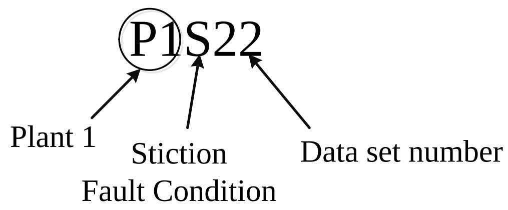
PI: Proportional Integral

SP: Set point

VSD: Variable speed drive

LIST OF SYMBOLS AND ABBREVIATIONS FOR DATASET FILES AND ARTIFICAL NEURAL NETWORK SUMMATION FILES

DATA SETS



P1: Plant 1

P2: Plant 2

P3: Plant 3

S: Stiction fault condition

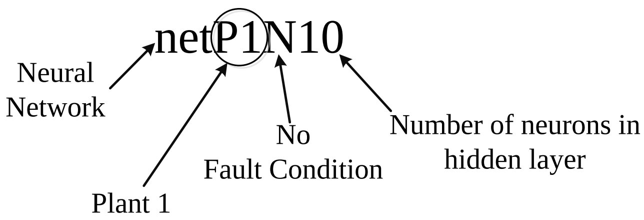
B: Backlash fault condition

L: Low air supply fault condition

N: No fault condition

H: Hysteresis fault condition

ARTIFICIAL NEURAL NETWORKS



Example: netP1N10: Neural network trained to detect the ‘no fault’ condition for Plant 1. The artificial neural network contains 10 hidden neurons per hidden layer.

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Poor control loop performance is one of the major problems experienced in the process control industry. Some of the common indictors of a poor performing loop are:

*Oscillations o*f *the MV around the SP* can be a result of internal factors such as problems with the FCE, poor control loop tuning. Changes in process conditions and cyclical interactions between loops are external factors that could also cause oscillations. *Sluggish Response* can be due to poor controller tuning, or deadband, hysteresis or damage in the FCE. *Random deviations from SP* can be as a result of noise from the transmitters, disturbances or problems with the FCE. Process control practioners and researchers are constantly trying to devise new methods of improving control loop performance which has a direct impact on plant efficiency and profitability. From the above discussion, one can surmise that most practical control loops do experience behaviours that would impact negatively on the performance. With this in mind, the research study will propose a method to diagnose some process fault conditions.

1.2 RESEARCH PROBLEM

A process control loop consists of a controller, sensor and a FCE. The degradation of any of these three elements will result in poor control loop performance [1]. The output of the controller is applied to the FCE. Any underside variance in the operation of the FCE will have a negative effect on the performance of the FCE. FCEs could be in the form of VSDs, pumps, motors and control valves, or any other device under control. For this study the control valve is considered as the FCE. The condition of the FCE is the major source of process variability and this will impact negatively on the performance of the control loop. The control valve is in direct contact with the process, therefore an underperforming control valve will yield an inferior product and an unstable system.

Maintenance of the control valves is usually done on a routine bases, at every plant production shut-down and control practitioners are however of the view that this is not the best way [2]. Surveys within the manufacturing industry have found that in many instances costly resources are often wasted on the unnecessary overhaul and maintenance of control valves [3].

With longer intervals between plant maintenance, the need for frequent monitoring of the valve's condition and control performance increases. Regular condition monitoring of a control valve's performance during a control session is essential in order to reduce the possibility of breakdowns attributed to a damaged control valve [4]-[6].

Historically, the state of a control valve was determined by decommissioning a control loop and then removing it for repairs and maintenance. The use of predictive maintenance for control valves is a proven way to improve process reliability and contributes towards the reduction of overall maintenance costs [7], [8]. Valve diagnostics systems make it possible to detect potential problems without removing the loop from service [2], [9], [10]. Control valves are an essential element of most process control loops and are usually referred to as the FCE [2],[11]. The condition of the FCE has a major impact on the control behaviour of a process control loop and impacts on plant productivity and hence company profit [2],[9],[12]. Given this, the main focus of this study will be on the control valve, and its performance during a control period.

1.3 AIM OF RESEARCH

The objective of this research is to develop a computational intelligent based diagnostics system using ANN's to assess the operating state of a process control valve. The software developed in this research is used to diagnose typical control valve problems such as stiction, backlash, hysteresis and low air supply. The control loop dynamic performance signature from a control session is used to develop a loop performance matrix which is then mined for the pertinent data vectors. These salient vectors are used to train the artificial neural network to detect the exact nature of the fault.The valve diagnostics system is developed for detecting control valve faults such as poor air supply pressure, stiction, hysteresis and backlash.

1.4 SCOPE OF RESEARCH

For this research the following aspects of control valve performance are considered:

- Dead band (Backlash)
- Stiction
- Hysteresis
- Low air supply

These four aspects were selected because they are the most common control valve problems experienced in the process control industry [13]. Nonlinearities found in control valves are discussed in more detail in Chapter 2.

1.5 RESEARCH METHODS

The following methodology was followed during the development of the CI based valve diagnostics system:

1. Recording of data corresponding to specific control valve fault signatures
2. Determining the impact of the control valve fault on the control loop signature.
3. Extraction of training and test data sets.
4. Identifying suitable CI based architectures and schemes for implementing the diagnostics system
5. Design, development, implementation and testing of the CI based diagnostics system.

1.6 CONTRIBUTION OF THE STUDY

Stiction, hysteresis, deadband and backlash are main sources of nonlinearities in process control valves. These loop faults were simulated on a mini plant and the data corresponding to each of these faults were used to train the ANN based diagnostic system for fault classification. Up and above the basic requirements for the study, the research also proposed two new methods for simulating control valve stiction and hysteresis. The simulated nonlinearities were tested on a mini plant utilising both open-loop and closed loop control configurations. These two new techniques eliminate the need to create complex models for closed-loop stability analysis and the investigation of compensation methods under dynamical conditions. A stickband compensator was also developed and applied to the plant for reducing stickband and limit cycle amplitude. The technique is based on a 'stickband-jacket' applied between the input and the output of the actual control valve. The feedback error signal is used to vary the width of the stickband and limit cycle frequency. Two international conference papers have been published based on this research and are listed:

1. Sewdass, S., Govender, P., 2013. Simulation of process control valve stiction, in: The International Conference on Composites, Bio composites and Nanocomposites. Presented at the ICCBN 2013, Durban.

2. Sewdass, S., Govender, P., 2014. Control Valve Stickband Compensator, in: Preprints of the 19th World Congress The International Federation of Automatic Control. Presented at the IFAC 2014, Cape Town.

These papers are included in the appendix.

1.7 STRUCTURE OF THE THESIS

A brief outline of current valve diagnostic software is given in Chapter 2. Chapter 3 discusses the sources of common nonlinearities found in process control loops. Thereafter Chapter 4 outlines compensation techniques for nonlinearities such as stiction and hysteresis. Chapter 5 introduces the Artificial Neural Network (ANN) and describes its suitability for the proposed valve diagnostic system. Chapter 6 outlines the process plant used to gather data. This data was used to train the ANN to detect fault conditions. Chapter 7 outlines the methods used to simulate the different fault conditions on the mini plant, and also describes the extraction of data sets for training the ANN system. Chapter 8 discusses the design of the ANN ensemble architecture. It also discusses the software that was written to create and train the ANN to behave as an ensemble based fault detection system. In Chapter 9 the analysis of the performance of each specialist in the ensemble is discussed. Chapter 10 summarizes the research, concludes and suggests future work.

This page is intentionally left blank

CHAPTER 2

CURRENT TECHNOLOGIES

2.1 INTRODUCTION

Control valve diagnostic software was first introduced in the 1980's where portable systems made use of external sensors to monitor the movement of the valve stem and the forces acting on the valve assembly [14]. In the 1990s digital valve positioners with microprocessors were used together with sensors to provide offline diagnostics [14].

The 21st century has seen the development of intelligent valve controllers for online valve diagnostics. These valve controllers had the added capability of analysing data from built in sensors, indicating deteriorating performance of the valve through alarms. Further enhancements in technology include the Metso Valve Manager and the Flow Scanner 6000 software.

2.2 METSO VALVE MANAGER SOFTWARE

The Metso valve manager software [15] for the valve controllers provide graphical display of the valve's performance parameters, which allows for preventative maintenance.

Table1.1 indicates the parameters that are made available when using the Mesto Valve Manager Software.

Control performance index	Indicates the performance of the whole control valve assembly and its task to control the flow in the pipeline.
Valve condition index	Presents the status of the valve based on its use, history and current measured values.
Actuator condition index	Presents the status of the actuator based on its use, history and current measured values.
Positioner condition index	Presents the status of the positioner based on its use, history and current measured values and also on several self-diagnostics parameters.
Environmental condition index	Takes into account the conditions of the assembly (e.g., supply pressure value and its steadiness) and also selected aspects of valve assembly configuration.

Table 2.1: The Mesto Valve Manager Indices [15].

The Flow Scanner 6000 is a portable valve diagnostic system that can help evaluate the performance and assist in the calibration of all makes and models of control valves using wireless or Ethernet communication.

The Flow Scanner 6000 Valve diagnostic system [16] has six test options which are presented below:

Dynamic Scan test is used as a performance benchmark for other tests. The control signal is varied between two points and data is recorded during the up and down stroke. The data is then analysed for dynamic valve operation.

Static Point Scan steps the control signal and records the valve travel. The data recorded on up and down valve stroke of the valve is used to determine hysteresis and deadband.

Step Change test determines the valve stroking speed and dynamic response.

Stepped Ramp where small steps are used to test the valve response to process ramps.

Step Study tests indicate the valve's resolution and approximate deadband. This test also shows the effects of the total valve characteristics on process gain.

Sine test is used to conduct a frequency response analysis.

These test options enable the technician to have a comprehensive view of the valve's online performance [16].

2.3 SUMMARY AND CONCLUSION

Control valve diagnostic systems are constantly evolving with advancements in technology. HART Protocol and PROFIBUS telemetry allows for faster transfer of online control valve diagnostics with additional parameters. The current control valve diagnostic software enables users to save data of specific valves which helps to track the overall maintenance of the process control valve. Fuzzy logic is also applied in valve diagnostic systems to monitor the performance of process control valves [17]. Fuzzy logic has the ability to approximate fault conditions and improve overall performance of the diagnostic system [17]. Many new control valve diagnostics software have been developed and with advances in technology this developments are constantly been improved.

This page is intentionally left blank

CHAPTER 3

NONLINEARTIES IN PROCESS CONTROL LOOPS

3.1 INTRODUCTION

Mechanical, electrical, hydraulic and biological systems all contain nonlinear elements [18], [19]. For example, Ferromagnetic cores in transformers in electrical systems may contain nonlinear magnetization while frictional forces in mechanical systems may result in nonlinearities. Most process control loops contain nonlinear elements. An example of a nonlinear element in a control system is a transducer which may exhibit linear characteristics over a limited operating range and thereafter exhibit a nonlinear behaviour [19]. An example of a transducer that may exhibit this type of behaviour is a diaphragm pressures sensor or level sensor. Control systems may also have structural nonlinearities such as dead time because of long pipe lengths [18]. Nonlinearities in process control valves are common in industry and lead to degradation of system performance [20]. Stiction, hysteresis and dead band are common sources of nonlinearities in process control valves and the focus of this research is based on these nonlinearities.

3.2 BACKLASH (DEADBAND) NONLINEARITY

Backlash is present in every mechanical system and is caused by the looseness of mechanical parts. Backlash can occur in a control valve assembly and occurs after a valve changes direction. Its travel in the opposite direction does not correspond to what the control signal is calling for. Backlash manifests itself in the form of a deadband and an increase in the size of the deadband has a considerable effect on loop performance during a control session [21].

A valve experiencing dead band behaves as if there is some backlash between the controller output and the actual valve position. Every time the controller output changes direction, the dead band has to be traversed before the valve physically starts moving. Dead band can also be caused by excessive friction in the valve, an undersized actuator, or a defective positioner [22]. Some symptoms of control valve backlash are listed below:

1. Increase in dead time within the control loop due to a larger deadband [23]. The dead time appears as a result of a temporary discontinuity between the CO and PV, when the CO changes direction. The CO must overcome the deadband again when the CO direction changes before a change in PV can occur [24], [25]. Dead time becomes short if the control error is large. This is due to the presence of a larger CO which is able to quickly overcome the deadband [25].

2. PV may not reach SP when backlash is present. To a certain extent by introducing the reset/integral action, this may help reduce the offset [23].

The position of the backlash in a control loop using a control valve as the FCE is shown in Figure 3.1. With regards to Figure 3.1, the CO first goes through the backlash and once the CO overcomes the dead band, a true process input is sent to the process and results in the PV [23].

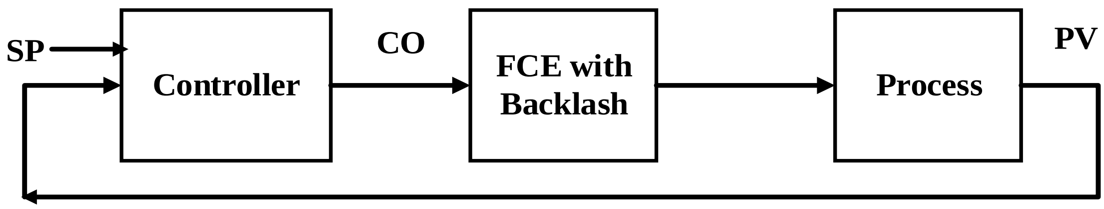


Figure 3.1: Control loop indicating the position of the backlash [23].

3.2.1 Mathematical representation of backlash

Backlash is a dynamic nonlinearity and the equation is therefore a complex valued function [23].

$$Re_a = \frac{1}{\pi}\left(\frac{\pi}{2} + \arcsin\left(1 - \frac{d}{a}\right) + \left(1 - \frac{d}{a}\right)\sqrt{\frac{d}{a}\left(2 - \frac{d}{a}\right)}\right),$$

$$Im_a = -\frac{d}{\pi a}\left(2 - \frac{d}{a}\right) \qquad \text{(Equation 3.1)}$$

With regard to Equation 3.1, *d* is the dead band due to backlash and *a* is the input amplitude. *Re* and *Im* refer to the real and imaginary components in a complex number, respectively. The magnitude of *d* will influence the amplitude of the limit cycling of the PV around the SP [23].

3.2.2 Phase plot representation for backlash

Figure 3.2 is the phase plot describing the input - output behaviour of a control valve experiencing backlash [25]. There are two phases in Figure 3.2, namely the deadband phase contoured within regions AB and CD, and the moving phase (region BC and DA).The valve stops at points A or C when the rate of change of the valve input is constant or minimum, or when CO changes direction. The valve will remain in this stuck position until the controller output increases to overcome the deadband; it then continues to travel during the moving phase.

For a type 2 control loop, a change in load conditions will result in offset. The integral controller compensates for this offset by varying the input signal to the valve. If the valve suffers from backlash, the initial change in CO will not cause a change in the PV [26]. A change in PV will only occur once the controller output increases to a point where it can overcome the dead band. For increases in dead band width, the control valve's ability to change position to smaller changes in CO will decrease. This reduces the performance of the valve and impacts negatively on the loop's control performance. A control valve with a large dead band will not respond to small changes in PV [27].

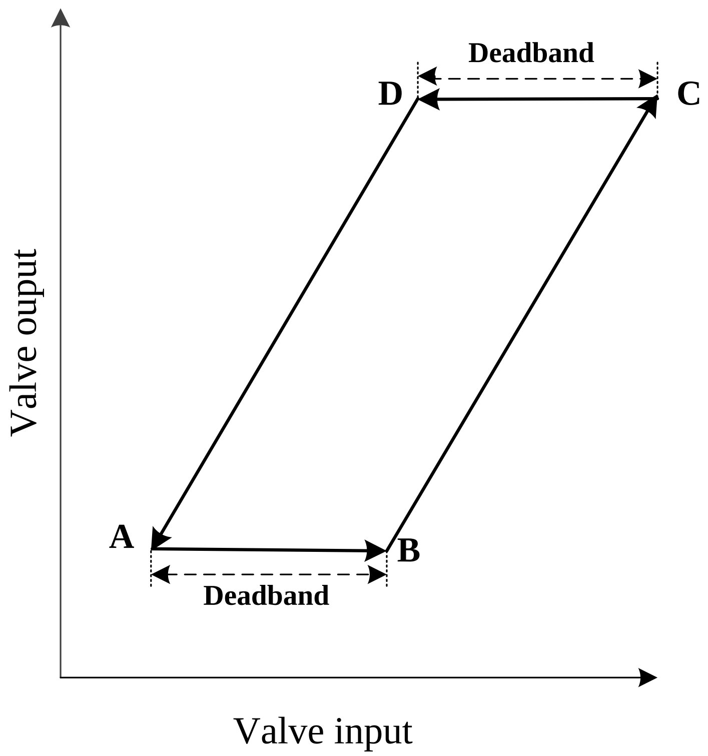


Figure 3.2: Input output behaviour of a valve with backlash [24].

3.2.3 Illustrating the effect of backlash on PV

The plant trend of a healthy control valve is compared to the response of a valve experiencing backlash in Figure 3.3. The effects of backlash on the loop's performance are twofolds, namely:

- An increase in dead time.
- The presence of a constant offset, preventing PV from reaching SP.

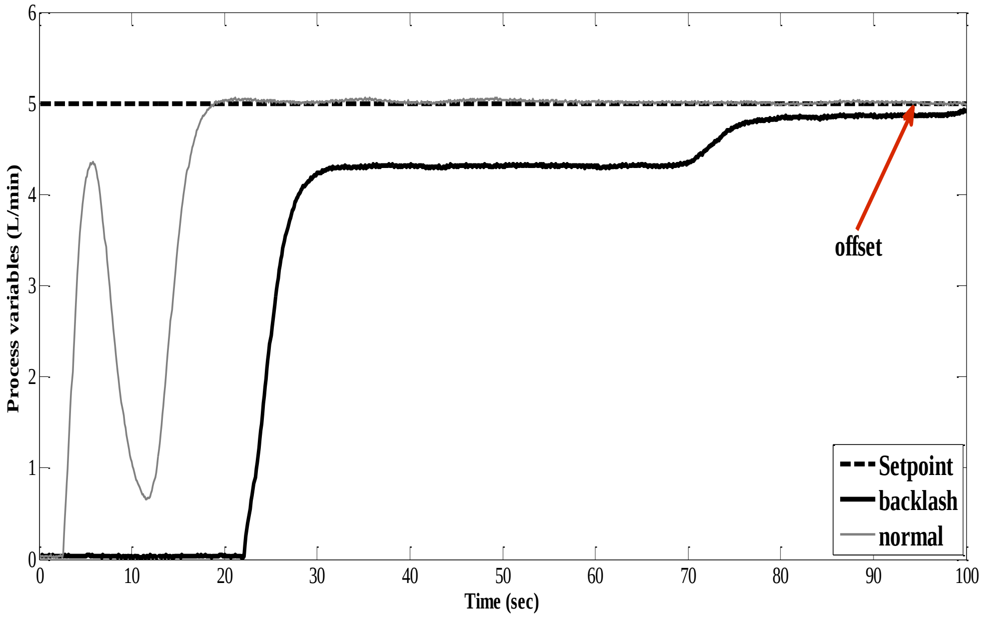


Figure 3.3: Closed loop response of a valve experiencing backlash.

3.3 STICTION

Friction is a force that exists between two moving parts which are in contact with each other and tends to oppose motion. Friction comprises of static friction and dynamic friction [27]. Static friction must be overcome before any movement occurs between the two parts. Stick/slip or stiction are terms used to describe static friction.

Stiction is a result of high levels of static friction in control valves and will exist in its packing, guides and bearings; for ball valves it is commonly caused by the valve seals and by the linings in butterfly valves. Stiction can also be a result of friction occurring in the valve's actuators [28]. Stiction restricts the smooth movement of a control valve and can lead to an under-performance of the control loop.

3.3.1 Control valve friction

The nonlinear characteristic for control valve friction is shown in Figure 3.4. With regards to Figure 3.4, Fs refers to the static friction and Fc denotes the dynamic friction. The magnitude of F_c is smaller than that of F_s. For any movement to occur, the stiction force has to be overcome first [29].

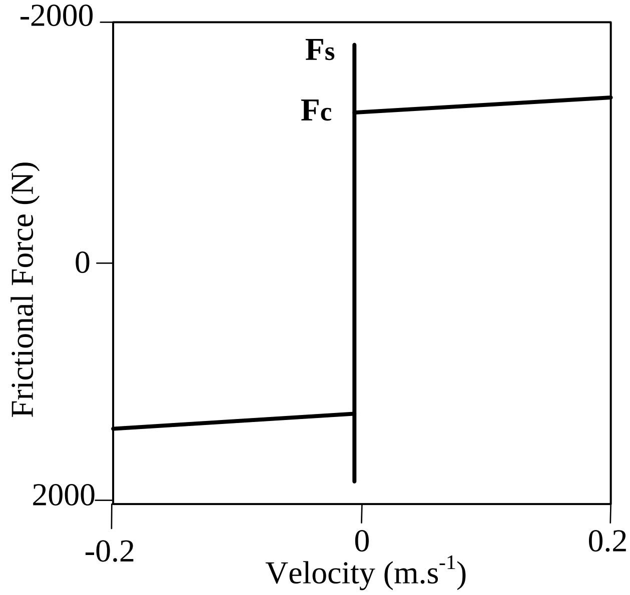


Figure 3.4: Characteristic friction plot [30].

3.3.2 Stiction and limit cycles

Stiction is one of the main causes of closed loop limit cycling [21]. Figure 3.5 represents the valve operating phase plot describing the input - output behaviour of a valve experiencing stiction. The following regions are outlined in Figure 3.5, the deadband and stickband (A-C and E-F), the slip jump (C-D and F-G) and the moving phase (A-G and E-D). With regards to Figure 3.5:

The control valve deadband and stickband is a result of the coulomb friction opposing valve movement [31]. The slip jump represents the sudden valve movement when the CO initially overcomes the deadband and stickband [31]. The moving phase represents the movement of the valve, which may occur when the valve's dynamic friction forces are lower than the static friction forces [31].

The valve will stick at points A or E, when it is at rest or changes direction. It will remain in the stuck position until CO is large enough to overcome the deadband and the stickband, and then continues to operate.

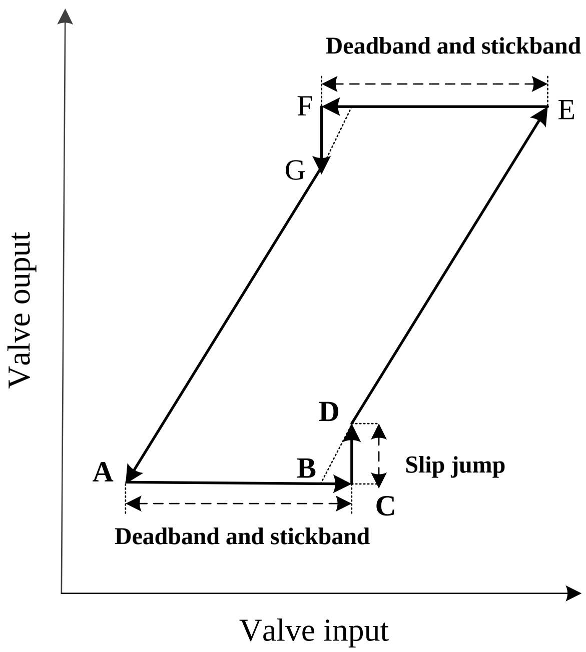


Figure 3.5: Input output behaviour of a sticky valve [30].

3.3.3 Mathematical representation of stiction

Choudhury et *al.* (2005) represents stiction as follows:

$$N = -\frac{1}{\pi X_m}(A - iB), \qquad \text{(Equation 3.2)}$$

where:

$$A = \frac{X_m}{2}\sin 2\emptyset - 2X_m \cos\emptyset - X_m\left(\frac{\pi}{2} + \emptyset\right) + 2(S - J)\cos\emptyset \qquad \text{(Equation 3.3)}$$

$$B = -3\frac{X_m}{2} + \frac{X_m}{2}\cos 2\emptyset + 2X_m \sin\emptyset - 2(S - J)\sin\emptyset \qquad \text{(Equation 3.4)}$$

$$\emptyset = \sin^{-1}\left(\frac{X_m - S}{X_m}\right) \qquad \text{(Equation 3.5)}$$

With regards to Equations 3.2 to 3.5:

Xm represent the controller output*;* *N* is the nonlinear gain and is represented by a complex equation where A is real and B is the imaginary component; *S* denotes the sum of the stickband and the deadband; *J* is the slip jump of the valve as indicated in Figure 3.5. $\emptyset$ is the angular frequency of the CO.

3.3.4 Effect of stiction on PV

The effect of stiction on a control loop is evident in the comparison of the trends of a healthy valve, to a valve experiencing stiction as shown in Figure 3.6. The PV exhibits a ‘squarish’ shape with poor set point tracking. The stickband and poor set point tracking is also evident in the plant response when stiction is present.

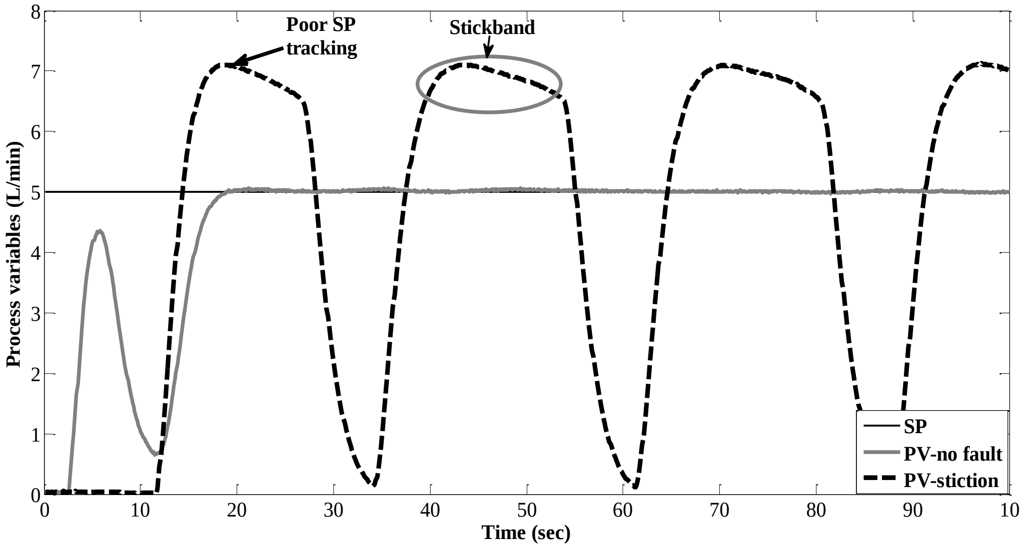


Figure 3.6: Closed loop response of a butterfly valve experiencing stiction.

3.4 HYSTERESIS

Hysteresis is defined as a nonlinearity which arises when materials having elastic properties do not return to their original shape and size after being stretched. Deadband is the dominant nonlinearity and hysteresis is a secondary effect [25]. Control valve hysteresis can be attributed to:

1. Dynamic friction between the control valve's stem and packing, and loose linkages [32].
2. A change in CO causes the valve diaphragm to deform and this damage is not reversed when the actuating force is removed.

Given this, we can therefore assume that hysteresis is a function of the valve's past dynamic behaviour. The control environment also has a direct impact on hysteresis, as it varies with temperature and the friction of internal components [33].

Hysteresis is represented by a double valued function shown in Figure 3.7 and is generated by making small incremental changes (approximately 5% to 10%) to the valve's input (CO) and then observing the change in the PV. With reference to Figure 3.7: The two curved branches represent the direction of the valve movement. The difference between valve opening and valve closing curves is an indication of the dissipated energy due to hysteresis [28].The positive slope of the straight line represents the valves linear region of operation. For no hysteresis, any change in CO will result in a corresponding change in PV. The error due to the hysteresis lies in the region between the curvature and the straight line. With hysteresis present, the 'curved' response of the graph arises due to the presence of the hysteresis nonlinearity. The curvature in the response is attributed to the fact that for a given in CO, there will not be a proportional corresponding change in PV, resulting in a nonlinear response.

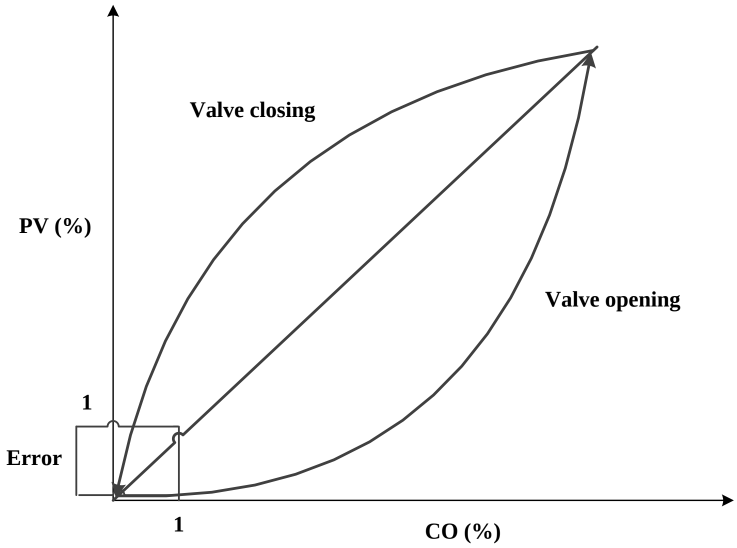


Figure 3.7:Hysteresis Curve [28].

3.4.1 Effect of hysteresis on the PV

The comparison of the plant trend of a healthy valve to a control valve with hysteresis is show in Figure 3.8. The presence of hysteresis increases the dead time and this results in the PV taking longer to reach the SP. Hysteresis also causes the PV to be less responsive to changes in CO, and also introduces limit cycling and poor SP tracking [34], [35].

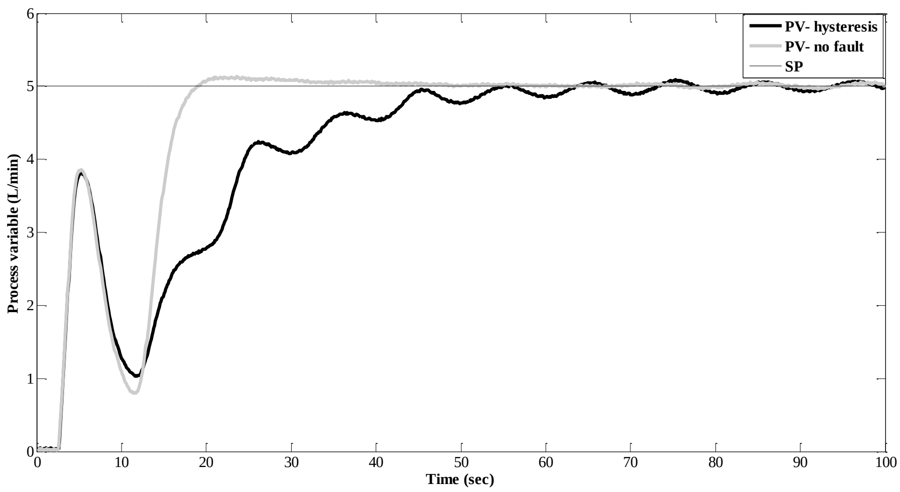


Figure 3.8: Closed loop response of a valve experiencing hysteresis (From Plant 1 *cf.* Appendix 2 page 135).

A controller sends a control signal to the control valve via a valve positioner and valve actuator to achieve precise control. Positioners that are defective or tuned too aggressively will cause the valve to overshoot and oscillate around the target. Positioner overshoot occurs when the valve moves too far and this can destabilize the loop [36].

3.5 LOW AIR SUPPLY

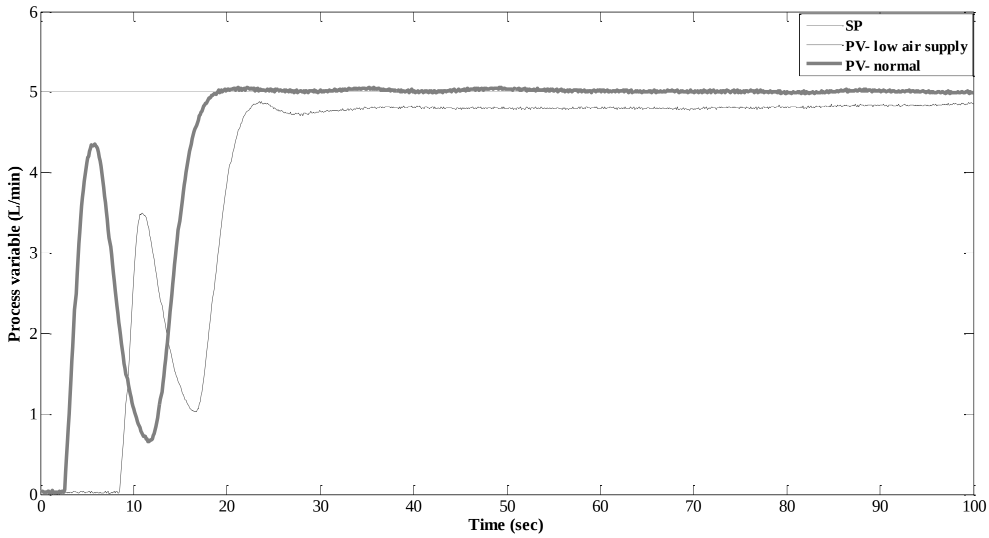


Figure 3.9: Closed loop response of a valve experiencing the low air supply fault (From Plant 1 *cf.* Appendix 2 page 135).

Based on experience, the low air supply fault is a common fault in a plant and is a result of high demand on the air compressor or a damaged air-line. This fault affects the amount of air sent to the valve actuator via the positioner and leads to a lag in the movement of the valve. From Figure 3.11 we observe that there is an increase in the dead time and offset as a result of the low air supply fault. The PV does not reach the set point.

3.6 SUMMARY AND CONCLUSION

This chapter outlined some of the common nonlinearities found in process control. The causes and the effects on loop behaviour due to stiction, hysteresis, and backlash were discussed. The next chapter discusses compensation techniques for nonlinearities in process control valves.

This page is intentionally left blank

CHAPTER 4

CONTROL VALVE NONLINEARITY COMPENSATION

4.1 INTRODUCTION

Nonlinearities exist in most real world control loops and create challenges for control practitioners [37]. The control valve is usually the most common cause of problems in real world process control loops [38]. Control valve nonlinearities can lead to undesirable gain effects, limit cycling and undesirable phase shifts during a control session [28]. The two most common control valve nonlinearities experienced in the process control industry are stiction and hysteresis. Given this scenario, commonly applied control valve compensation techniques are discussed in this chapter.

4.2 STICTION COMPENSATION

4.2.1 The knocker

Hagglund *et al*. (2002) proposed knocker pulses to be combined with the controller output to overcome the stiction nonlinearity (*cf*. Figure 4.1). The knocker pulse is introduced into the CO when the friction level is increased to a level at which stick slip occurs [39]. Stick slip is the phenomenon which occurs when a control valve experiencing stiction remains at rest (stick) and suddenly moves (slip) once CO is large enough to overcome the deadband due to stiction [30].

Hagglund's 'stiction knocker' pulse [39] is shown in Figure 4.1. With reference to Figure 4.1: The level of the pulses gradually increases due to the integral control action. This result in a gradual pressure build-up within the actuator until the valve element frees itself from the stuck position.

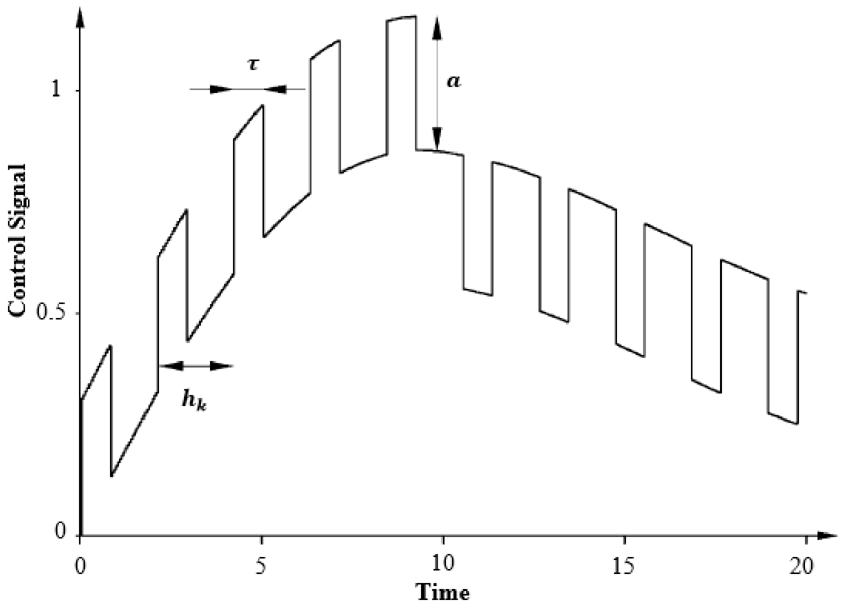


Figure 4.1: Control signal with knocker [37].

Figure 4.2 illustrates the topology of the control loop with the stiction compensator.

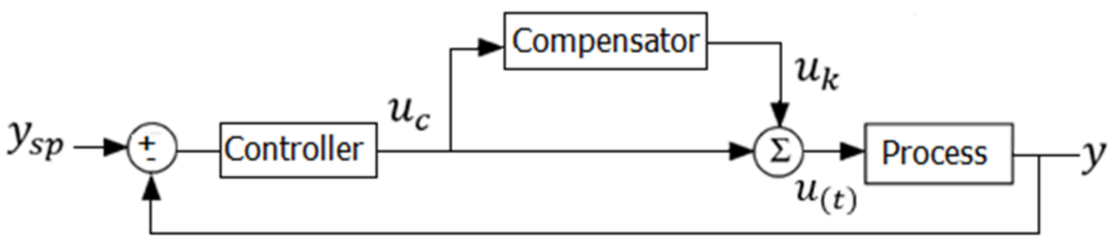


Figure 4.2: Control loop with compensator mechanism [39].

The control signal applied to the process is the algebraic sum of the knocker pulse and the controller action (*cf*. equation 3.1) [39]

$$u(t) = u_c(t) + u_k(t) \qquad \text{(Equation 4.1)}$$

With regards to Equation 4.1: $u(t)$ is the control signal, $u_c(t)$ is the output from the controller and $u_k(t)$ is the output from the knocker.

The output from the knocker $u_k(t)$ is a pulse sequence having three parameters [39]:

- The time between each pulse (h_k)
- The pulse amplitude (a)
- The pulse time constant (τ).

During each pulse interval:

$$\mathrm{u_k}(t) = \begin{cases} a\ sign\left(u_c(t) - u_{c(tp)}\right) & t \le \left(t_p + h_k + \tau\right) \\ 0 & t > (t_p + h_k + \tau) \end{cases} \qquad \text{[39] (Equation 4.2)}$$

With regards to Equation 4.2, t_p is the initial time of the previous pulse, therefore the sign of each pulse is determined by the rate of change of the control signal $u_c(t)$.

With regards to Figure 4.2, the transfer function between the knocker output and

the process for $t > \left(t_p + h_k + \tau\right)$ will be :

$$\frac{Y}{u_k} = \frac{G_p}{1+G_pG_c} \qquad \text{[39] (Equation 4.3)}$$

With regard to Equation 4.3, G_p and $\mathrm{G_p}$ are the transfer functions of the process and the controller, respectively. If $u_k(t)$ is a pulse with amplitude (a) and width (τ), then the process output becomes reference:

$Y = \frac{G_p}{1+G_pG_c}(1\text{-}e^{-s\tau})\frac{a}{s} \approx \frac{G_p}{1+G_pG_c}\ a\tau$ [39] (Equation 4.4)

Therefore the disturbances are proportional to the product $a\tau$ which determines the energy of each pulse in the knocker [39].

The addition of the knocker to the CO can result in a more aggressive control valve stem movement, which leads to an increase in the valve wear, thus reducing the valve's operating life span [40].

4.2.2 The two move method

The two move method was proposed by Srinivasan and Rengaswamy (2008) and requires knowledge of the control valve's stem position in order to reduce process variability [41]. Figure 4.2 outlines the basic topology of the control with the stiction compensator in place. The compensating signal U_k is added to the output of the controller u_c and is shown in equation (4.5)[42]:

$u(t) = u_c(t) + sign\left(\frac{du_c(t)}{dt}\right) U_k(t)$ (Equation 4.5)

According to Srinivasan and Rengaswamy (2008), the compensator causes two movements of the valve.

Movement 1: The initial signal (U_k (t)) moves the stem from the stuck position as defined by equation (4.6) [42].

$U_k(t) = |u_c(t)| + \propto d$ (Equation 4.6)

With regards to equation (4.6), d is the stickband and $\propto$ signifies a real number.

Movement 2: The second signal from the compensator moves the stem to its steady state position in order to remove the error [42].

$$U_k(t+1) = -u_c(t+1) \qquad \text{(Equation 4.7)}$$

After the second stem movement, the stem does not move from this steady state position since the CO is cancelled by Equation 4.7 and the signal sent to the valve is constant [42]. Since deviation variables for all measurements are assumed, their respective steady state values are zero; for the second valve movement, $x(t) = 0$ will make PV = SP [42]. In the author's opinion this is only theoretical and will not occur easily in real processes.

The two movement defining equation in equation (4.8) was developed by assuming that control valve behaviour is predicted using the valve's stickband [42]:

$$x(t) = \begin{cases} x(t-1) & if\ |u(t) - x(t-1)| \leq d \\ u(t) & otherwise \end{cases} \qquad \text{(Equation 4.8)}$$

With regards to (4.8): $x(t)$ and $x(t-1)$ are the present and past stem movements, respectively; $u(t)$ represents the present controller output and d is the stiction band. This compensation method requires the valve position to be steady and this is difficult to attain in most real world processes [42].

4.2.3 Stickband Compensator

The stickband compensator method proposed by Sewdass and Govender (2014) is based on Glattfelder's and Schauffelberger's (1986) technique where an "anti-windup jacket" is placed around the model of the saturation nonlinearity to minimise the effect of the nonlinearity on the loop performance. Glattfelders and Schauffelberger's (1986) technique reduces the impact of integral windup which occurs when the integral controller calls for a control action that the valve is not capable of producing and results in cycling. This anti-windup jacket technique is used to reduce the width of the stickband in control loops experiencing stiction nonlinearity.

Figure 4.3 is a schematic of the proposed stickband compensator.

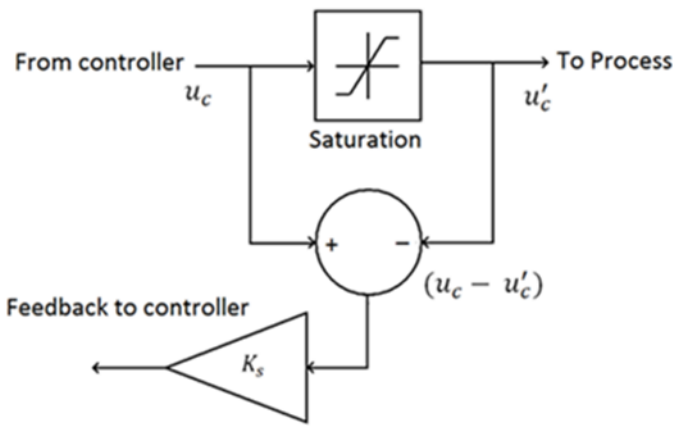


Figure 4.3: Stickband compensator [43].

The controller output (u_c) is compared to the process input signal (u_c) and results in the stiction error(e'). The gain of the compensator is K_s is a user adjustable parameter to reduce stickband width. The algorithms of the compensator with an ideal PID controller are defined as follows [43]:

$$U_{PI}(t) = K_p e(t) + \int_{t0}^{tf} [K_i e(t) - K_s(u_c - u_c')]dt = K_p e(t) + \int_{t0}^{tf} [K_i e(t) - K_s e'(t)]dt \quad (4.9)$$

$$U_{PID}(t) = K_p e(t) + \int_{t0}^{tf} [K_i e(t) - K_s e'(t)]dt \quad + K_d e(t)dt \qquad \text{(Equation 4.10)}$$

With regards to Equations (4.9) and (4.10): $u_c$is the controller output, u'_c is the output from the valve and $e(t)$ is the instantaneous error signal.K_s is the gain of the compensator and by using it in the feedback loop, moves the control from 1-degree of freedom to 2-degree of freedom. From Equation 4.11 we see that the compensator gain increases, the loop response converges faster with increased oscillation [43].

$$K_s = \begin{cases} > 1 & high\ oscillation\ frequency\ with\ reduced\ stickband \\ < 1 & increased\ stickband\ with\ low\ oscillating\ frequency \\ 1 & optimal\ setting \\ 0 & zero\ compensation \end{cases} \qquad \text{(Equation 4.11)}$$

4.3 HYSTERESIS COMPENSATION

To the best knowledge of the author, the research and literature on control valve hysteresis is still very limited and the author is of the opinion that there is much opportunity for research in this area of control and process engineering for developing a hysteresis compensator. Following an exhaustive search by the author of several databases, only 1 publication by Tao and Kokotovic (1995) was available on this topic [44]. Tao and Kokotovic (1995) made use of a parametrized hysteresis model was to develop an adaptive inverse hysteresis for plants with unknown hysteresis [44]. An adaptive controller together with the inverse hysteresis model is used to cancel the effects of hysteresis. The controller and inverse hysteresis parameters are updated to compensate for a wide degree of hysteresis [44].

4.4 SUMMARY AND CONCLUSION

This chapter outlined a few stiction and hysteresis compensation techniques. A new effective stickband compensation method was also introduced. Closed and open loop plant test with the compensator indicate a reduction in the size of the stick band which results in the reduction of oscillation amplitude with an increase in limit frequency. This compensator technique is discussed in more detail in Sewdass and Govender (2014). The next chapter introduces the Artificial Neural Network (ANN) which was used to classify faults in the diagnostics system.

This page is intentionally left blank

CHAPTER 5

ARTIFICAL NEURAL NETWORKS

5.1 INTRODUCTION

Artificial Neural Networks (ANN's) fall within the artificial intelligence (AI) paradigm. Systems that possess AI display human characteristics such as emergent behaviour, adaptability and the ability to learn. AI falls within the domain of soft computing. Soft computing systems are computationally intensive and require high speed processors plus substantial quantities of RAM for fast and efficient processing. ANN's are modelled on the biological nervous systems and consist of elements which are massively interconnected basic elements called neurons. Today ANN's are used to solve problems in engineering, medicine, commerce and in fact in any other application where sufficient data is available for processing.

5.2 ANN ARCHITECTURE

An elementary neuron is described by the following equation:

$$a = f(wp + b) \qquad \text{(Equation 5.1)}$$

With regards to Equation 5.1 the neuron output a, is determined by the product of the transfer function (f) with the weight (w), input (p) and the bias (b). The neural network is trained by adjusting the weight and bias (collectively referred to as the ANN's 'free parameters') to perform a specific task for a specific input. Training data is used to train the network to match network outputs. The network will continue training until the user specified training goals or the numbers of iterations are met.

With regards to Figure 5.1: The input into a neuron (p) has a weight (w) which is updated during training and converges when the goal is reached. The neuron bias (b) is a parameter that is used to set the level of pre-knowledge for the neuron. The initial value of the bias is usually influenced by the pre-knowledge of the designer of the system. The dot product of the weight and input vectors is algebraically summed with the bias and applied to the transfer function (f).

ANN's are available in 2 basic configurations, namely feedforward ANN (FF-ANN) and recurrent ANN's.

Feedforward ANNs contains one or more hidden layers with an output layer and allows signals to travel in one direction from input to output (*cf.* Figure 5.2) [45].

Recurrent ANN's contain feedback connections from the output of the hidden layer to the input. The feedback allows the network to evolve by using the previous network output as an input, this allows the network to perform more complicated tasks (*cf.* Figure 5.3).

These configurations are used extensively in process control applications such as process model identification, model based predictive control and nonlinear control.

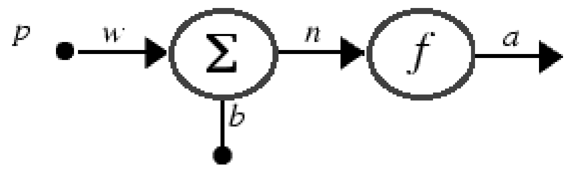


Figure 5.1: An artificial neuron [45].

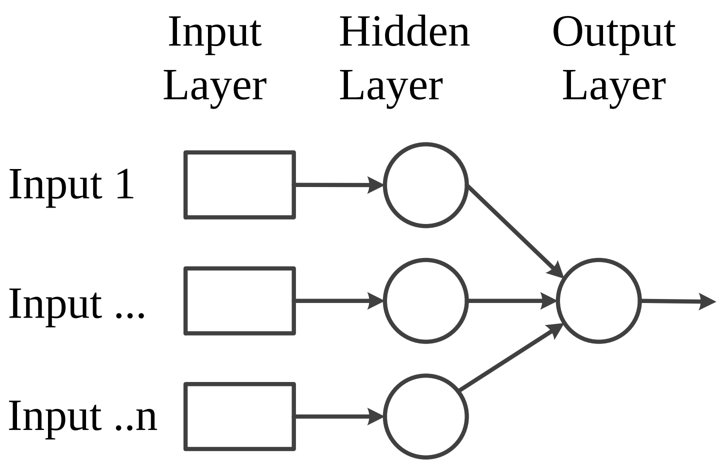


Figure 5.2: Feed forward ANN [45].

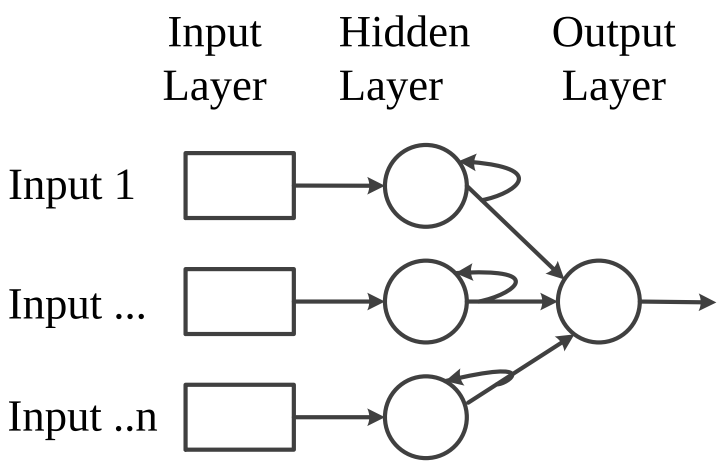


Figure 5.3: Recurrent ANN [45].

5.3 ANN CHARACTERISTICS

ANN's possess the following characteristics:

1. **Ability to accommodate nonlinearities**

   Most real life problems are nonlinear in nature and ANN's with nonlinear transfer functions can be trained to accommodate these nonlinearities.

2. **Input output mapping:**

   An ANN can be trained to associate outputs with inputs. There may be differences between the actual output and the desired output. During training, the free parameters of the network are adjusted to reduce this difference and thus obtain an output which is closest to the desired output.

3. **Adaptability**

   The neural network has the ability to learn. There are two types of learning, one through a teacher and the other through association. The teacher indicates the desired output for specific inputs. The ANN learns during training. Using a training method such as backpropagation, the values of the free parameters are adjusted till the actual output is much closer to the desired output. This characteristic will enhance the performance of the ANN in the diagnostic system as plant environmentally conditions may change.

4. **Fault Tolerance**

   The ANN are inherently fault tolerant and are able to function in spite of some non-critical neurons having damaged neurons or faults [46].

5.4 ANN TRAINING METHODS

The process of training an ANN involves the adjustments of the strengths between connecting neurons in the network by a learning algorithm. The three main training (learning) methods are:

Supervised Learning: The ANN is trained to match inputs to a specific output (target). The targets are provided by the user.

***Unsupervised Learning**:* The ANN is trained to respond to salient features of the inputs and develops its own representation of the inputs [47].

Reinforcement Learning: is a combination of supervised and unsupervised learning, where the learning process is continuously graded and adjustments to the network weights are made until the ANN is successfully trained [48].

5.5 ANN TRAINING ALGORITHM

There are different types of training algorithms, each suited for a typical application and network architecture. The backpropagation algorithm is one of the most widely used training algorithms for feedforward networks. This training algorithm monitors the gradient of the ANN performance function and adjusts the ANN's weights and biases during ANN learning to achieve a minimum performance [45].

The following are a few variations of the backpropagation algorithm:

- **Gradient descent algorithm:** The ANN's weights and biases are adjusted towards the negative gradient of the performance function [45]. This algorithm can be used in both batch or incremental training mode, the response is a bit slower.

- **Gradient descent with momentum:** The network's weights and biases are adjusted according to the local gradient, the *momentum constant* and the *learning rate*. The *momentum constant* prevents the network from been stuck in a shallow local minimum [45]. The learning rate affects the speed of the ANN's convergence. Training is faster than the basic gradient descent algorithm.

- **Levenberg-Marquardt algorithm:** updates weight and bias values according to Levenberg-Marquardt optimization which is a combination of the gradient descent and the Gauss-Newton training algorithms. The LM algorithm uses the gradient descent for the initial parameter selection and thereafter switches to the G-N method. Once it approaches the minimum goal the LM algorithm transforms to the gradient descent algorithm for improved results. The gradient descent has fastest training algorithm for networks of moderate size and has memory reduction feature for use when the training set is large.

The training of the network will stop when any of the following conditions occurs:

- **Epochs:** is the number of iterations during training process. An epoch represents a single presentation of all the training data to the network [45]. Training stops when the number of iterations exceeds epochs [45].
- **Goal:** the desired performance goal reached.
- **Time:** the set duration to train network is exceeded.

- **Minimum gradient:** Minimum performance gradient. Training stops when the magnitude of the gradient is less than the minimum gradient.
- **Maximum validation failures:** performance has increased more than maximum fail times since the last time it decreased [45].

Additional training parameters:

- **Learning rate**: is an additional parameter used to determine the changes to the weights and biases. Too large a learning rate will result in unstable training and if the learning rate is reduced to very small value it will result in the network converging at a slower rate [45].

- **Momentum constant:** is set between 0 and 1 and influences the updating of the current network weights after each iteration during network learning. This parameter can be used to prevent the error from been stuck at local minimum [45].

5.6 SUMMARY AND CONCLUSION

ANNs have the ability to detect trends and patterns from imprecise data that humans are unable to see. This ability makes them suitable for the proposed valve diagnostic system. The next chapter outlines the plant used to gather data; this data was used to train the ANN to detect fault conditions.

This page is intentionally left blank

CHAPTER 6

PROCESS PLANT

6.1 INTRODUCTION

A process control plant was used to develop the ANN based diagnostics software proposed in this study. The mini plant had to emulate the behaviour of one existing in a real world industrial environment. The flow rate was extracted from the plant for training the ANN based diagnostics system. Flow is a fundamental variable in most process control systems and was used to develop control valve signatures to indicate the operating condition of the control valve. The plant used in this research is discussed in more detail below.

6.2 PROCESS PLANT USED IN THIS STUDY

The process and instrumentation drawing of the plant used for this research is shown in Figure 6.1. The plant consists of a storage tank, flow transmitter, pump and a control valve. An electro pneumatic valve positioner is used to position a pneumatic butterfly valve in order to control the flow of water into the process tank. A Krohne IFC 100 electromagnetic flow transmitter is used to measure the flow rate of water into the process tank.

An Advantech PCI 1710 data acquisition card is used together with the Matlab to control the plant. The Advantech Software works well with Matlab and is easily configured in Matlab using the Data Acquisition Toolbox.

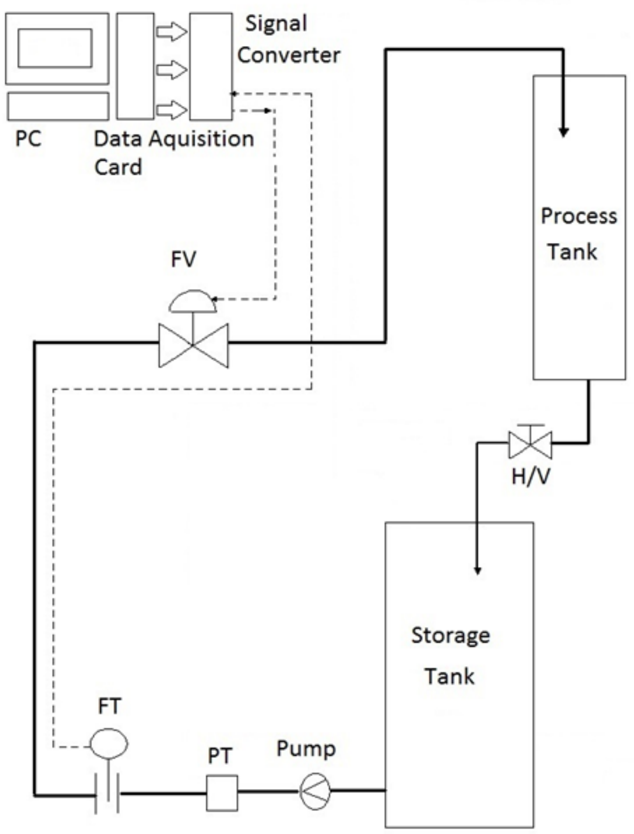


Figure 6.1: Plant overview [43].

Voltage to current signal convertors are used to interface the data acquisition card to the plant. The output signal to the control valve is shown in Table 6.1, where CO is the controller output and V is the voltage output from the PCI 1710 data acquisition card; the corresponding 4 to 20 mA current signal for each voltage level is also given in Table 6.1. The 4 to 20 mA signal is the input to the control valve.

The measurement range on the flow transmitter is adjusted to 0-10 l/min which corresponded to an output signal of 4 to 20mA. The flow rate of 1 l/min on the transmitter is calibrated to correspond to 1 unit in the Matlab environment as shown in Table 6.2.

CO	V out from Data Acquisition Card	mA signal from V/I converter
0	0	4
2.5	2.5	8
5	5	12
7.5	7.5	16
10	10	20

Table 6.1: Analogue output signals to control valve.

mA signal from flow transmitter	V out from I/V converter	Matlab Graph Display (l/min)
4	0	0
8	2.5	2.5
12	5	5
16	7.5	7.5
20	10	10

Table 6.2: Analogue signals from flow transmitter.

6.3 PLANT TUNING

The control loop has to be properly tuned in order to eliminate the possibility of poor loop tuning from masking the actual fault conditions. The control loop was tuned using the Ziegler-Nichols (1942) open-loop tuning method. A more detailed discussion of this method can be found in [19]. The method utilises the response’s time constant (process lag) and dead time characteristics to determine tuning parameters. For the sake of completeness, all the dynamics present in a loop’s transient response are discussed below.

6.3.1 Transient response characteristics

The transient response characteristics of a control loop describe its behaviour following application of an input stimulus. The response is characterised by dynamics such as a process lag, dead-time, time delay and oscillations. A step input signal has been chosen for this work because it is commonly used as a set point input in process control loops. The transient response of a system to a step signal stimulus is given in Figure 6.2. The characteristics are described below:

Delay Time: the time required for the response to reach half its final value.

Rise Time: is the time required for the response to rise from 10% to 90%, 5% to 95%, or 0% to 100% of its final value. The rise time is calculated using the following equation, $t_r = \frac{1}{w_d}\tan^{-1}\left(\frac{w_d}{-\sigma}\right) = \frac{\pi-\beta}{w_d}$ [19] (Equation 6.1).

Peak Time: is the time for the response to reach the first peak of the overshoot, the peak time is calculated using the equation the following equation, $t_p = \frac{\pi}{w_d}$ [19] (Equation 6.2) .

Maximum percentage overshoot: is the maximum peak value of the response curve measure from unity. The maximum percentage overshoot indicates the stability of the system and is calculated by the following equation, $M_p = \frac{C(t_p)-C(\infty)}{C(\infty)}$ [19] (Equation 6.3).

Settling time: is the time required for the response curve to reach and stay within 2% of the final value and is calculated as follows, $t_s = \frac{4}{\xi w_n}$ [19] (Equation 6.4).

It was necessary to tune the loop because the process control loop required a response that was as near optimal as possible. An optimised closed-loop response would yield data that could be used as an appropriate reference when training the ANN detection system.

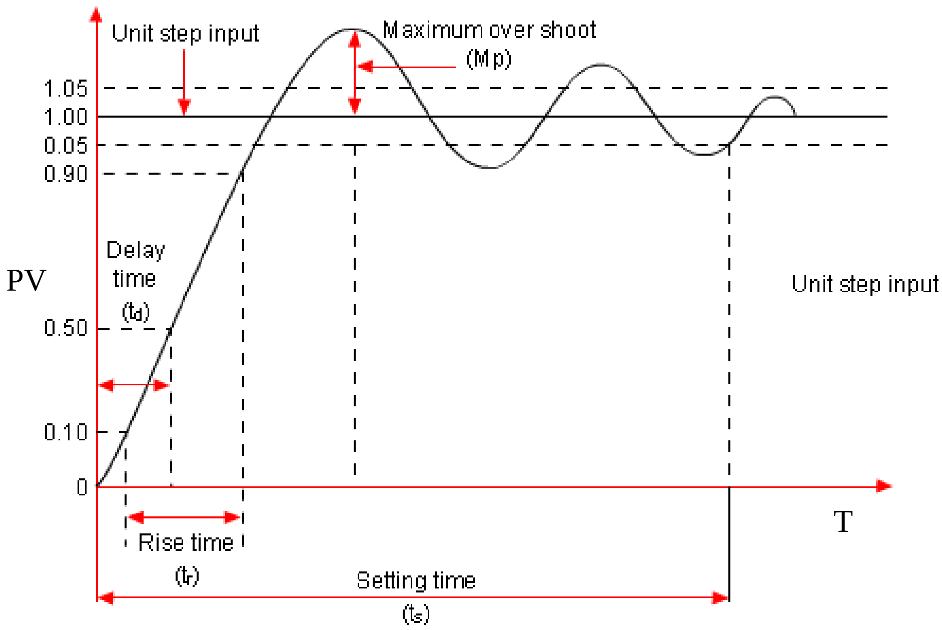


Figure 6.2: Transient response following a step input stimulus [49].

6.3.2 Creating the plant mathematical model

Data to create the plant's mathematical model was obtained by placing the loop in manual control mode and then directly applying a step signal to the control valve. The flow response data is then saved in a Matlab workspace and exported into the Matlab's System Identification Toolbox environment. The system was approximated as a first order system. A first order model was chosen since it is the fundamental building block of any system and replicates most of the salient dynamics present in higher order systems.

The open loop step response is show in Figure 6.3 and its associated transfer function is shown in Equation 6.5. The system identification toolbox requires some basic knowledge of the plant in order to generate an appropriate model of the plant and was used to approximate an open loop stable model for the loop under consideration.

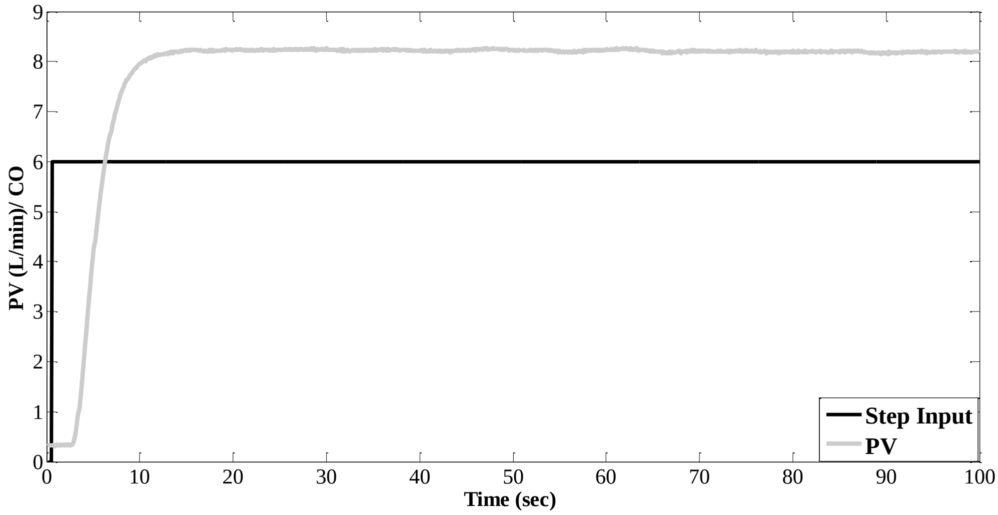


Figure 6.3: Open Loop step response.

The transfer function model for the plant is given in Equation 6.5.

$$G_{(s)} = \frac{K}{1+Tps} e^{(-L_p s)} \qquad \text{(Equation 6.5)}$$

With regards to Equation 6.5:

K = Gain = 1.2264 ± 0.00032659

$Tp1 = \text{ time constant } (or\ process\ lag) = 1.69376\ \pm 0.013884$

$Lp = dead\ time = \ 2.6256\ \pm 0.0071987$

The values were generated using the Matlab System Identification Toolbox.

The Ziegler Nichols tuning rule for open-loop systems is based on the step response of the plant and is used to tune the flow control loop. A tangent line at the point of inflection of the S shaped is drawn to determine the dead time L_p and a time constant T_p which worked out to 2.62 and 1.78 respectively (*cf.* Figure 6.4). The dead time and the time constant are used to determine the tuning parameters for the PI controller are shown below:

$$Kp = 0.9\left(\frac{T}{L}\right) = 0.9[1.78 \div 2.62] = 0.61145038$$

$$Ti = \frac{L}{0.3} = 2.62 \div 0.3 = 8.733$$

$$Ki = \frac{Kp}{Ti} = 0.61145038 \div 18.733 = 0.070013402$$

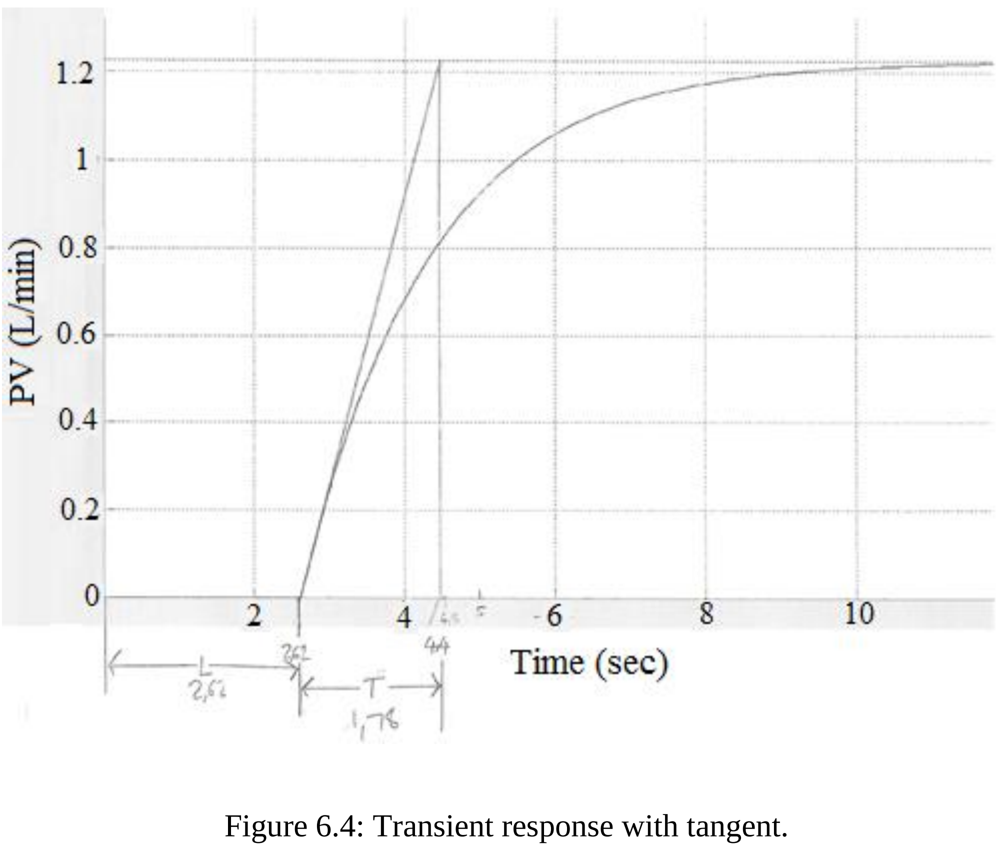


Figure 6.4: Transient response with tangent.

The Ziegler-Nichols open-loop tuning method provides initial parameters for loop tuning and does not yield satisfactory closed-loop response as is evident in Figure 6.5 where the flow rate fluctuates around the set point. To improve the close-loop response, the gain values can be divided by the 1.5 to 2 to minimise the oscillations. There is a distinct improvement in the loop performance and this is evident in Figure 6.6. The PV settles on the set point with reduced oscillations.

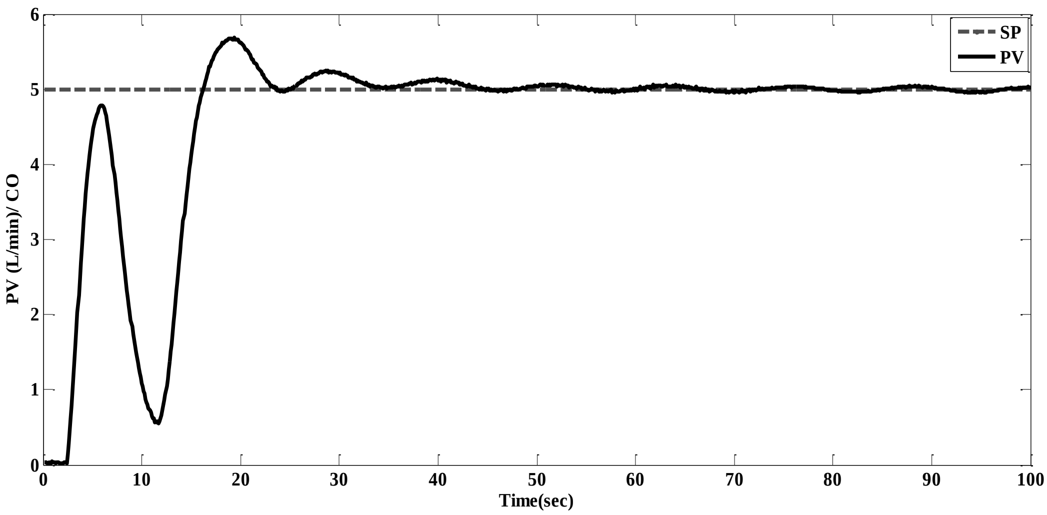


Figure 6.5: Closed loop response to step input signal.

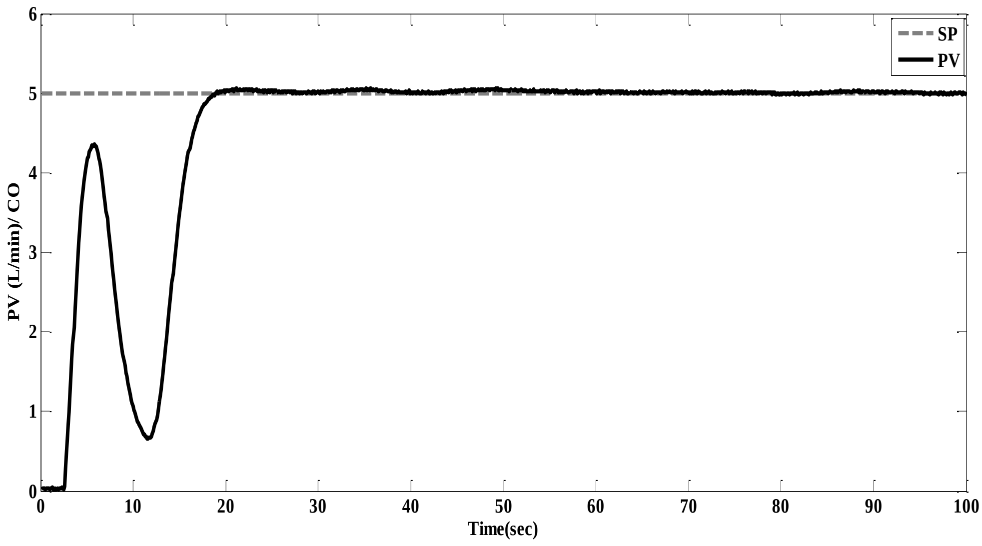


Figure 6.6: Closed loop response for of a tuned loop.

6.4 SUMMARY AND CONCLUSION

The mini plant discussed in this chapter was commissioned in the laboratory and was used to collect data for training the proposed ANN based control loop fault diagnostic system. The next phase of the research, which involved the simulation of typical control loop faults, will be discussed in the following chapter.

This page is intentionally left blank

CHAPTER 7

CREATING THE ANN TRAINING DATA SETS

7.1 INTRODUCTION

The proposed ANN based diagnostic system requires data sets of fault conditions and normal operating conditions. These data sets were used to train the ANN to identify fault conditions. This chapter outlines the methods used to simulate the different fault conditions on the mini plant and also describes the collection of data sets for training the ANN system.

7.2 EXTRACTION OF TRAINING DATA SAMPLES

The Simulink model in Figure 7.1 connects the Matlab environment to the process plant via a data acquisition card. The 'health' of the plant was thoroughly checked for faults such as poorly calibrated transmitters, poorly performing control valves and correct air pressure. Necessary steps such as calibration of the loop elements and loop tuning was performed to ensure that all the loop elements were performing accurately. Once this was verified, data samples of flow were collected for use as the training data for the ANN diagnostic system. Figure 7.2 shows the closed loop response of the plant when no fault conditions were present and Figure 7.3 represents the correlation plot. With reference to Figure 7.2 and Figure 7.3, the PV initially rises up to point A in response to the CO and then decreases to point B. The PV then rises once again to point C before settling at SP. This initial swing in PV is due the aggressive nature of the proportional action of the PI controller used in this control loop. The integral action of the PI controller causes the PV to reach SP.

The data corresponding to Figure 7.2 represents the ideal condition and was used as the benchmark for training the ANN system to detect the absence of a fault condition. The discussion on the response data can be found in chapter 8. Data for different plant fault conditions that were used to train the ANN system will be discussed in the next chapter.

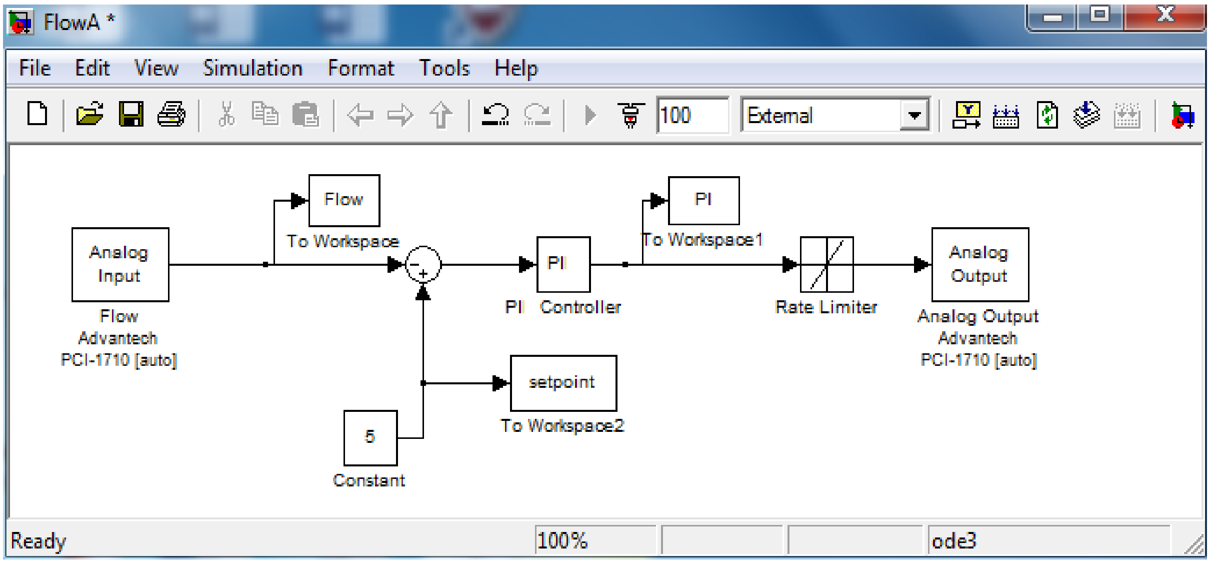


Figure 7.1: Closed loop Simulink model for flow.

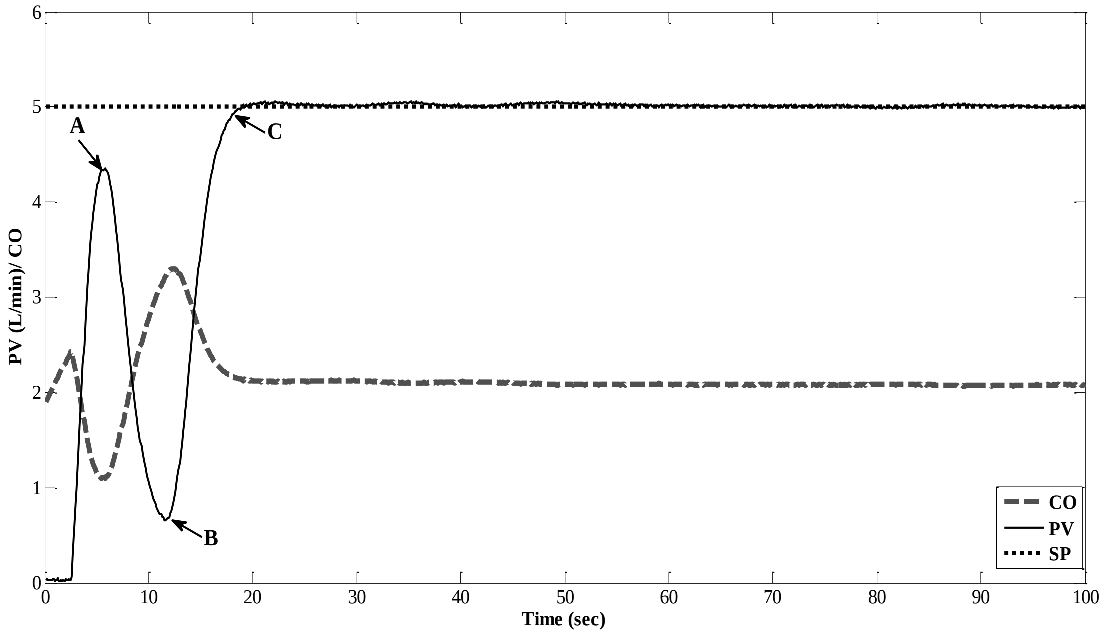


Figure 7.2: Plant trend for no fault condition.

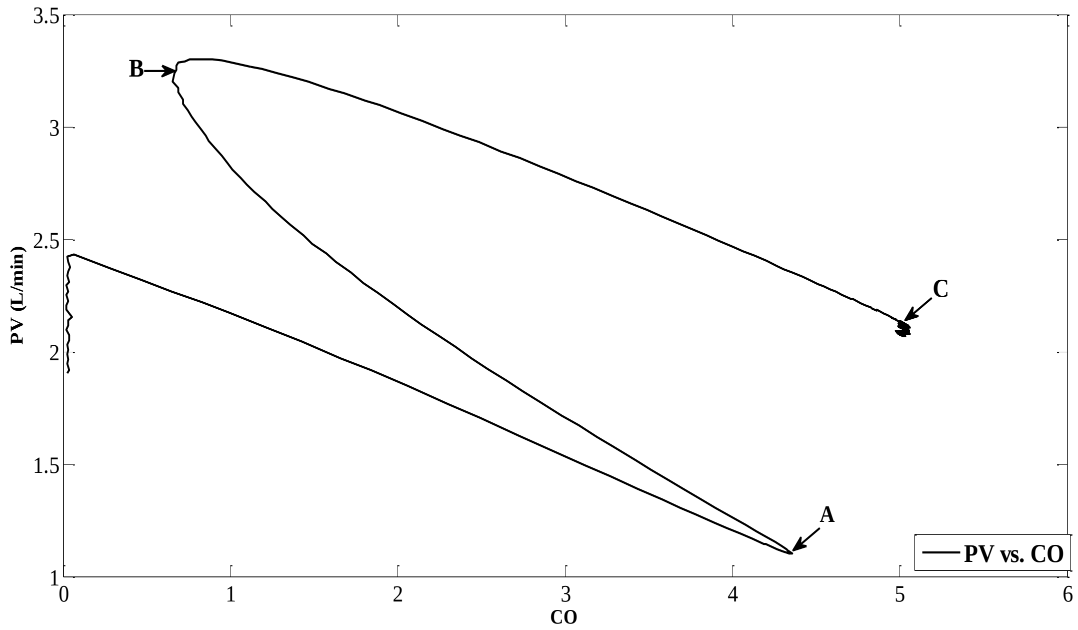


Figure 7.3: Correlation plot for no fault condition.

7.3 DEVELOPMENT OF CONTROL VALVE FAULT SIGNATURES

As mentioned previously in our discussion in chapter 3, typical common loop faults such as control valve backlash, stiction, hysteresis and low air supply were considered for the proposed diagnostics system. A brief description of how the data corresponding to these fault conditions is given in the following sections.

7.3.1 Control valve backlash fault

The tuned flow control loop is used as a starting point for the simulation of control valve faults. The plant on which this study was performed did not have any loop elements where backlash could be easily detected. For this reason it became necessary to create a simulation model for backlash using the Matlab Simulink toolbox. The backlash Simulink block model in Figure 7.4 was used to simulate the backlash fault in the control loop. The backlash model was configured in series with the plant's butterfly control valve. The Simulink backlash model had user defined parameters to adjust the width of the valve's 'deadband'. The deadband represents the region within which the valve remains inactive even when the controller signal is changing.

Figure 7.5 shows the comparison of flow responses for varying deadband width. From the responses, we observe that as the width of the deadband is increased, the resulting flow rate takes a longer time to reach the SP. The flow rate does not change initially and the control action continues to increase until the dead time due to backlash is overcome. For this research a range of 25 samples are collected, each having a different dead band. Figure 7.6 indicates the correlation between the CO and MV.

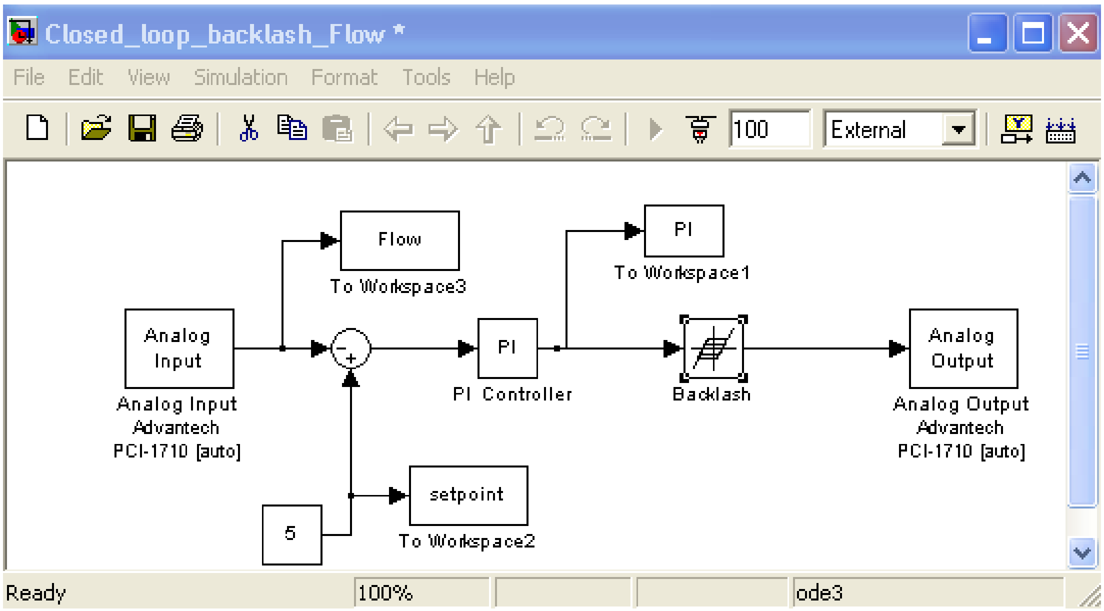


Figure 7.4: Simulink Model for Backlash.

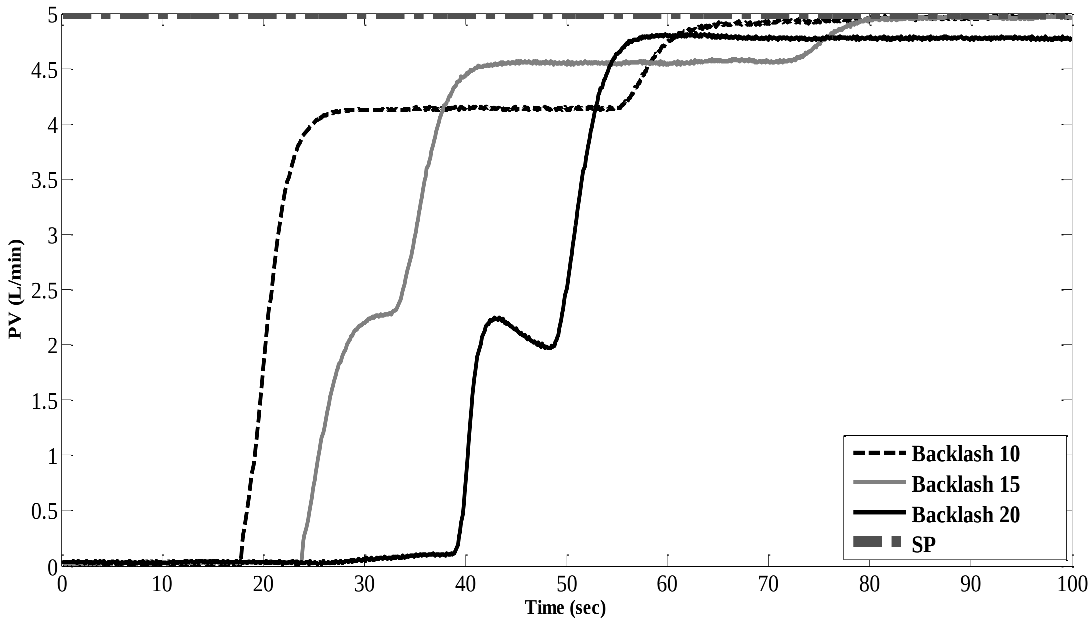


Figure 7.5: Plant trend of the backlash fault.

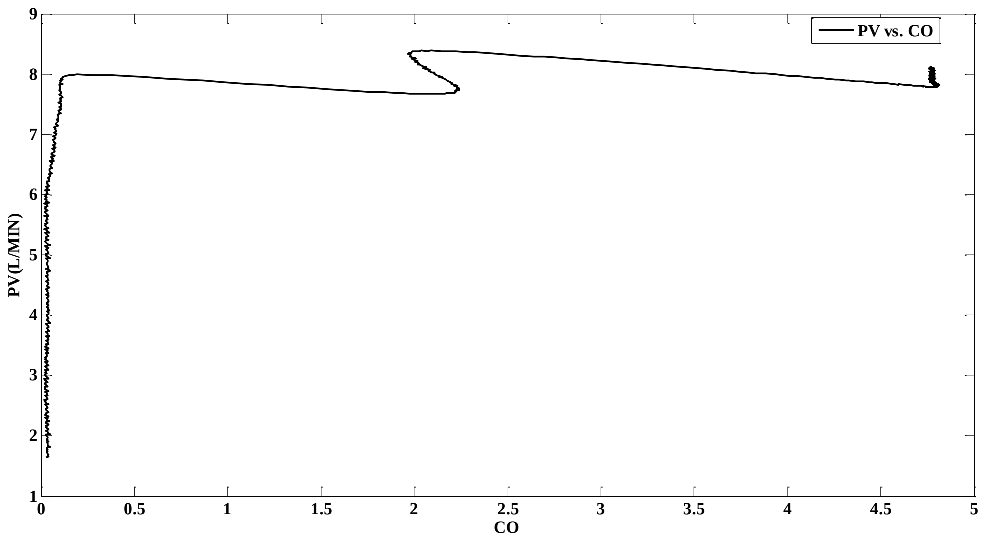


Figure 7.6: Correlation plot for no fault condition.

7.3.2 Control valve stiction fault

Stiction usually occurs when a valve's packing is over-tightened during a maintenance cycle, or is a result of high levels of static friction in the valve's actuators. Stiction can also exist in bearings in rotary motion valves, seals in ball valves; it can also be caused by damaged linings in butterfly valves. An electro- pneumatic valve positioner is used to position a pneumatic butterfly valve via a pneumatic actuator. The positioner's cam is attached to the positioner feedback shaft and the rotary actuator main shaft. The cam is part of the positioner that influences the stroke of the actuator.

The control valve's inherent characteristic can be adjusted by altering the cam. For this study, the obstruction shown in Figure 7.7 was inserted on the cam in order to alter the valve characteristic and hence simulate valve stiction. Bearing movement in a clockwise direction along the cam is hindered by the added obstruction. Valve motion occurs till the bearing reaches the obstruction. At the point of obstruction, the valve will remain stationary until the controller output overcomes the stick band of the valve. The valve then moves abruptly to the new position as a result of the build-up of pressure in the actuator. The valve experiences a similar slip jump phenomenon when returning to the closed position [50].

A tuned PI control loop was used to obtain the closed loop response. When stiction occurs, the output from the PI controller ramps up until the force is big enough to overcome the static frictional forces and the valve then moves to its new position. From Figure 7.8, we observe that stiction induces a limit cycle with a characteristic saw tooth shape in the CO and a square wave in the PV. The limit cycling of the PV is due to the offset between the set point and PV.

The correlation plot given in Figure 7.9 shows the elliptical trajectories with a flat region and sharp turn-around points. The flat region is due the valve's dead-band combined with its stickband [51],[52].

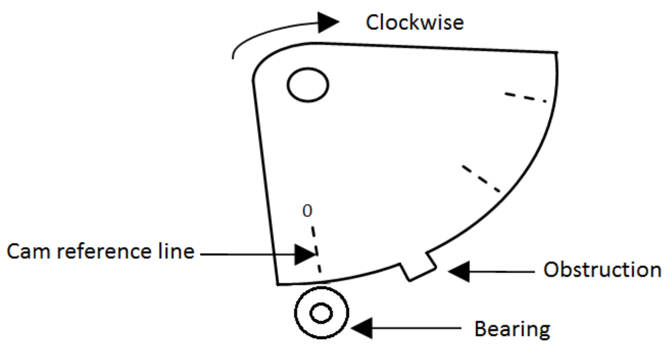


Figure 7.7: Cam with modification [50].

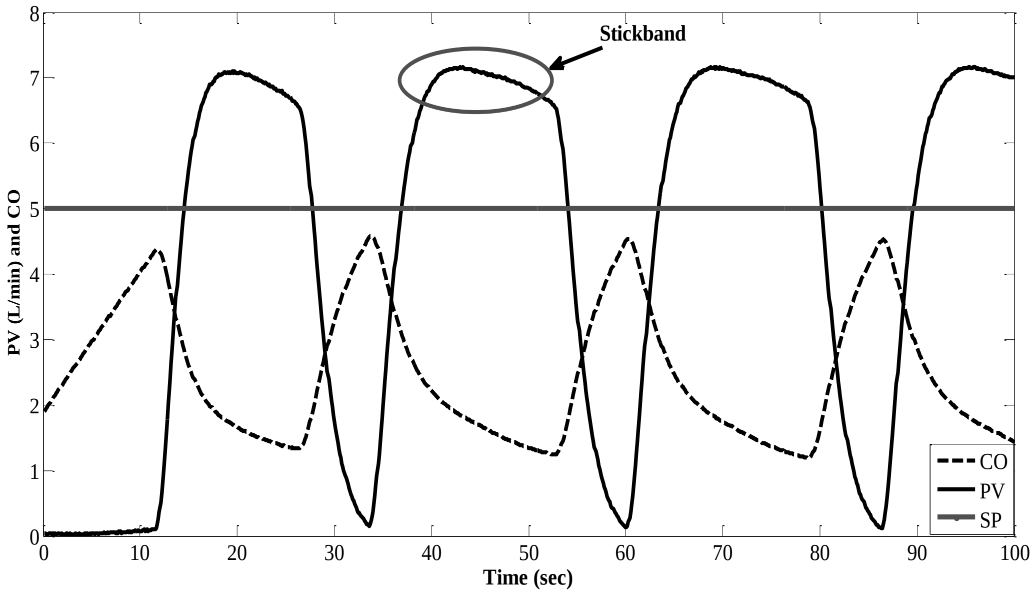


Figure 7.8: Closed loop response [43].

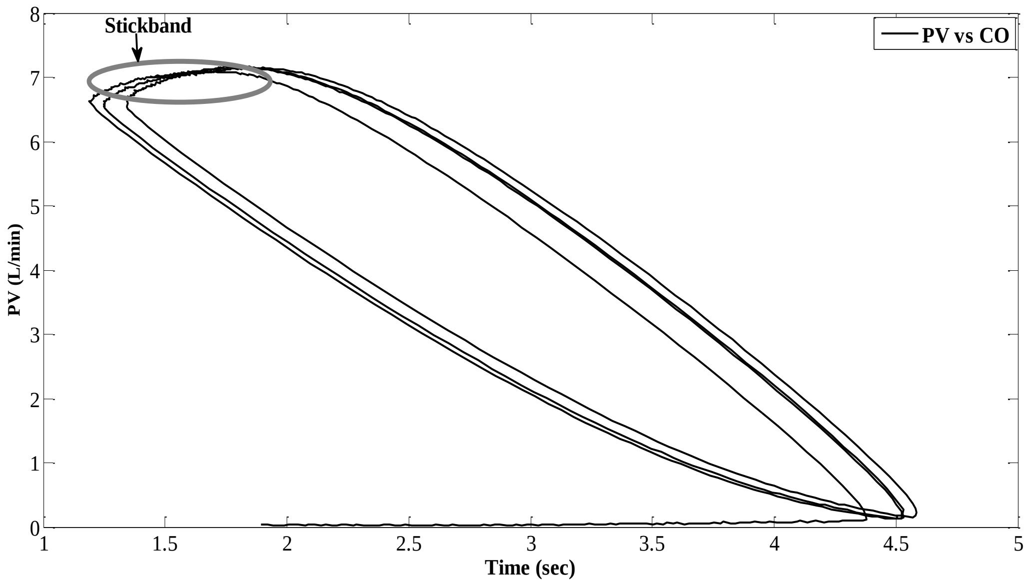


Figure 7.9: Correlation diagram [43].

From Figure 7.10 to Figure 7.13, we observe the following:

- Oscillation amplitude increases with stiction size because of increased CO.
- Dead zone size increases with stiction (*cf*. Wdb2 and Wdb1 on Figure 7.10 and Figure 7.12, respectively).

- Limit cycle frequency reduces when stiction increases due to the larger dead-band plus stickband (cf. Pb1<Pa1 and Pb2 <Pa2 on Figure 7.10 and Figure 7.12, respectively). This could be a positive effect depending on one's point of view. In the author's opinion, increasing the size of the stiction makes the loop more stable since the loop oscillation frequency is reduced; the down side though is the reduction in loop controllability due to the larger deadband.

With regards to figure 7.10 to figure 13 the impact of the stiction on the closed-loop performance varies proportionally with the size of the cam obstruction. The impact of the changes to the cam's operating characteristics on closed-loop performance confirms the presence of stiction.

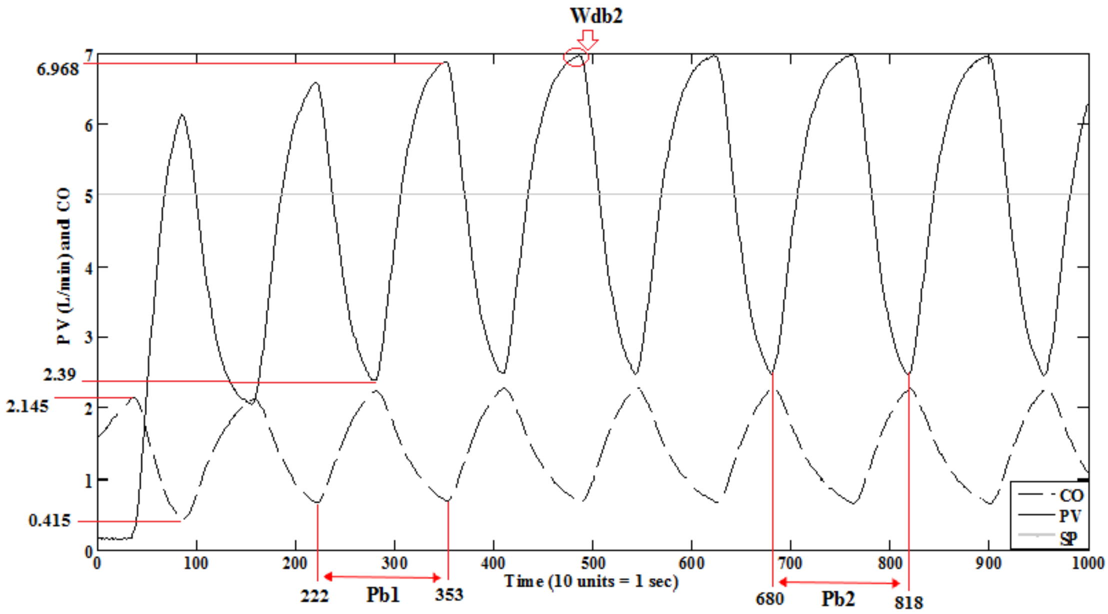


Figure 7.10: Closed loop response (weak stiction) [50].

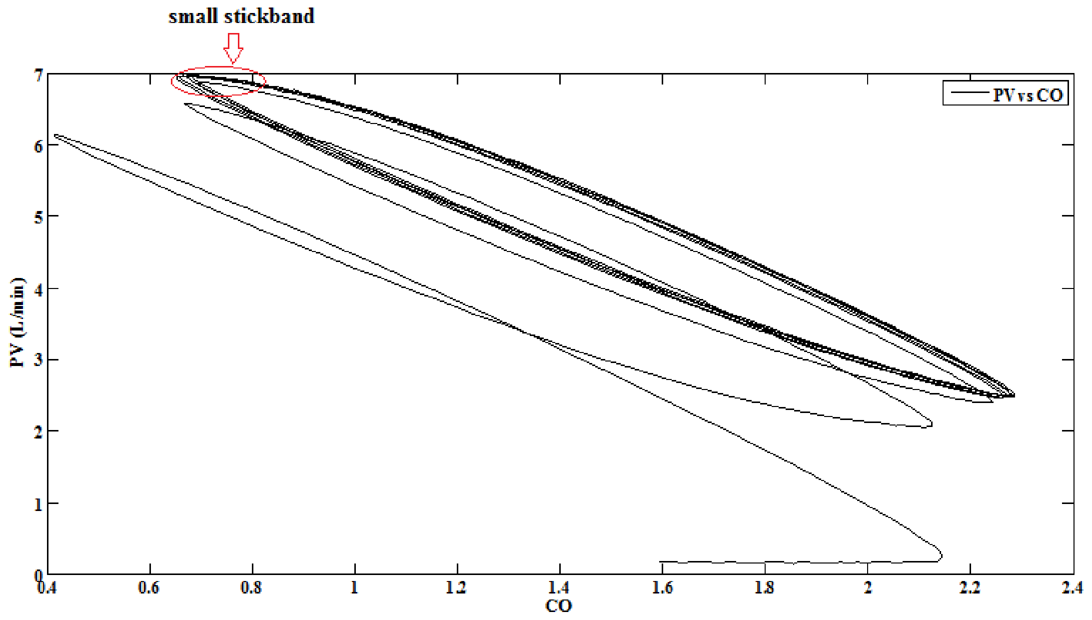


Figure 7.11: Correlation plot (weak stiction) [50].

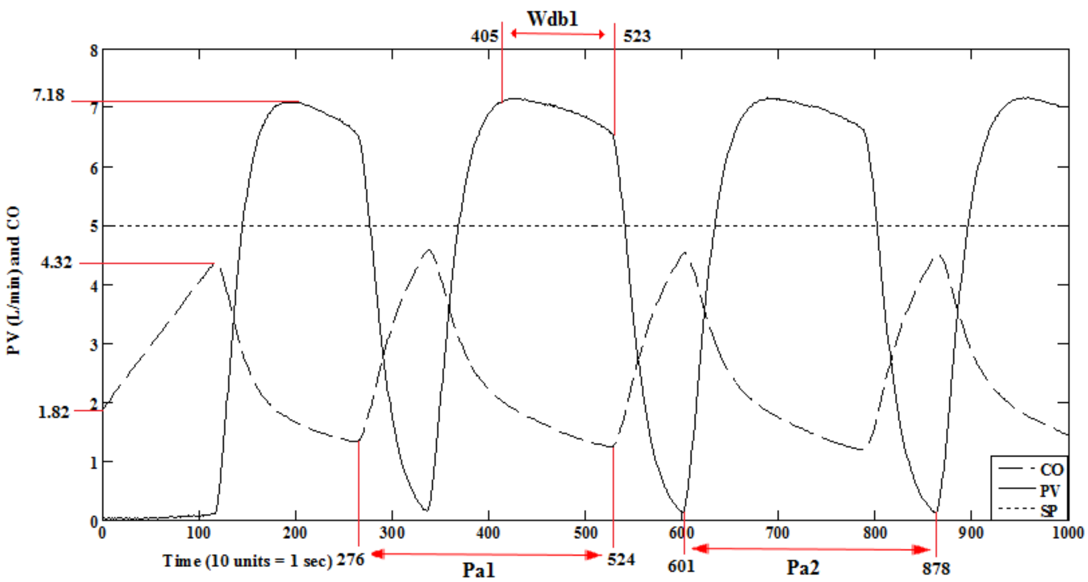


Figure 7.12: Closed loop response (increased stiction) [43].

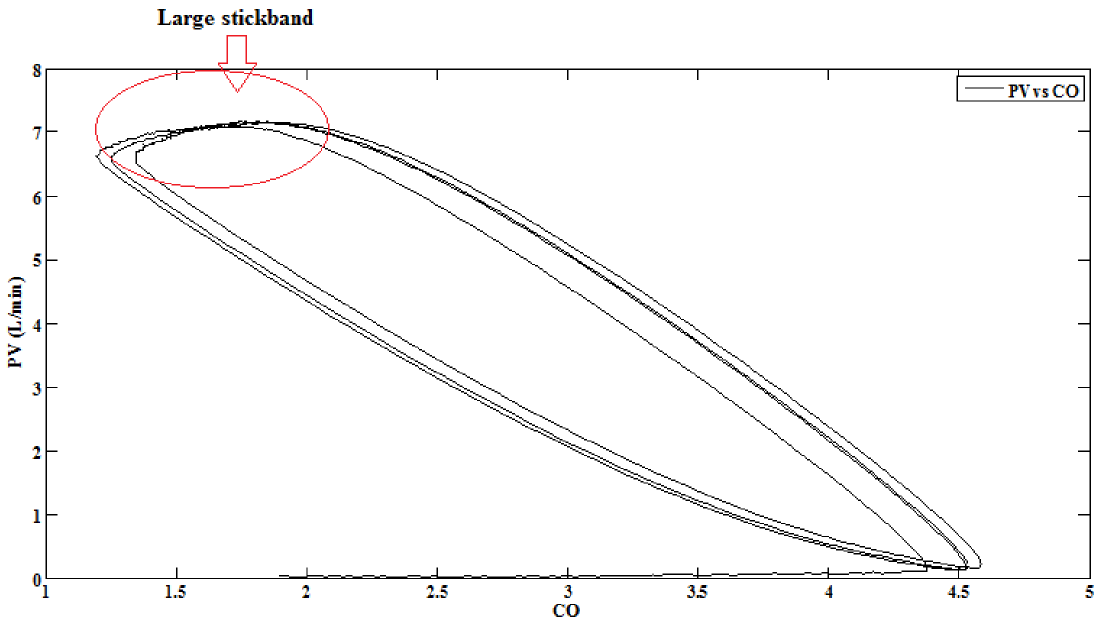


Figure 7.13: Correlation plot (increased stiction) [50].

7.3.3 Low compressor air supply fault

The compressor air pressure to supply the pneumatic valve positioner was limited via an air regulator to simulate a low air supply fault condition. The recommended operating range of air supply to the valve positioner and actuator is 300kPa to 800kPa. The air supply was regulated to the 68kPa to 275kPa range and a random range of samples were gathered. Figure 7.14 shows a random sample of the plant’s responses for two different values of low air supply. From Figure 7.14 we notice that there is an increase in the dead band with a decrease in the quantity of air supplied to the control valve positioner and actuator. There MV also takes a longer time to reach SP. The large deadband is also evident in the correlation plot (*cf.* Figure 7.15).

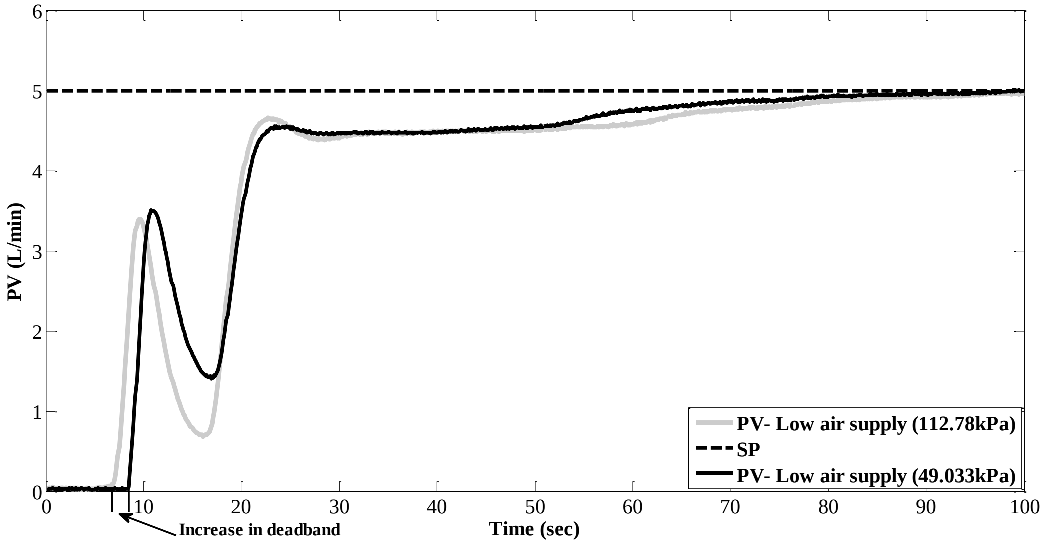


Figure 7.14: Control valve signatures with the low air supply fault.

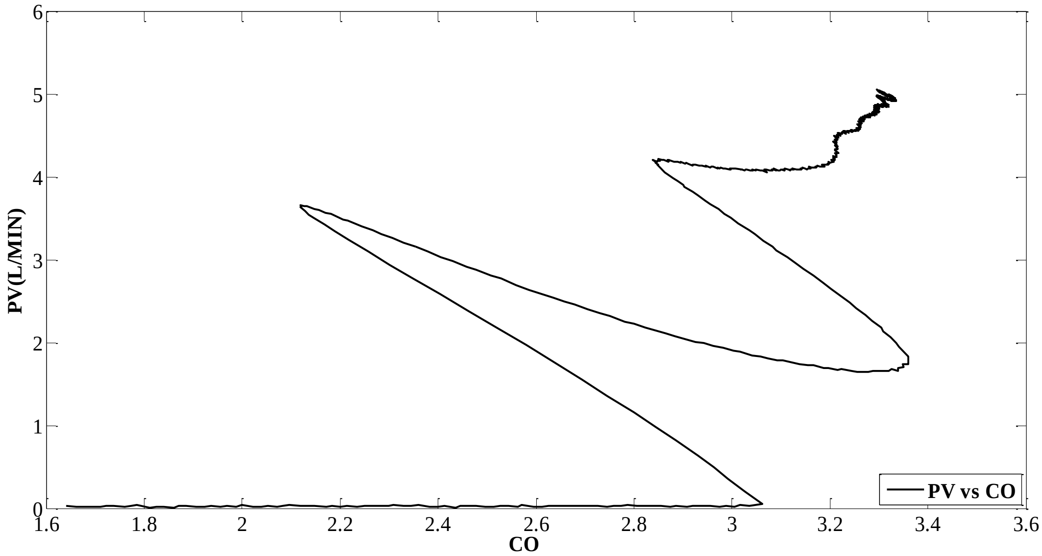


Figure 7.15: Correlation plot of low air supply fault.

7.3.4 Control valve hysteresis fault

The Matlab Simulink Toolbox, version 7.1 used in this study does not have a hysteresis model in its library. Extensive literature searches were also done by the author to find a suitable hysteresis model that would be compatible with Matlab. These searches were fruitless. Because of this, the author has had to create a Simulink model to simulate the control valve hysteresis within a process loop. The hysteresis MATLAB Simulink model in Figure 7.16 was created to simulate control valve hysteresis. The Simulink *relational operator* is used to compare the CO signal from the PI controller to the CO signal having a delay. This was done in order to determine the rising and falling edges of the control signal. Once the falling edge is detected a flip flop is activated. The output from the flip flop is then used to activate a switch. The switch is used to add a constant value (0.7) to the controller output only during the falling edge of the controller output. The 0.7 constant was heuristically determined during the design and test phase of this hysteresis model.

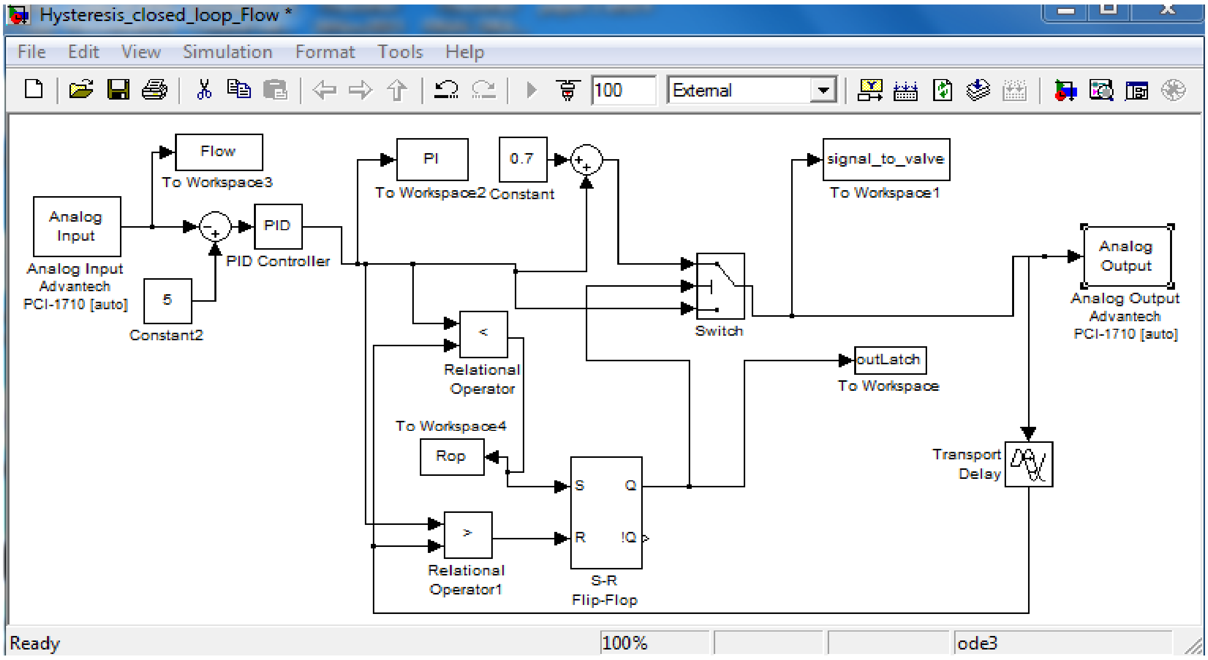


Figure 7.16: Simulink hysteresis model.

From Figures 7.17, a rising change in CO from 20% to 40% results in a 0.85 l/min change in PV; a reversal of CO from 40% to 20% results in a 0.3 l/min change in PV instead of 0.85 l/min. This difference in the flow rates for the same magnitude of CO confirms the presence of valve hysteresis [53].

Under closed-loop conditions, the periods Pa > Pb in Figure 7.18 confirms the presence of hysteresis as an increase in period indicates hysteresis [54]. Hysteresis also induces limit cycling around the SP is evident from the oscillation seen in both Figures 7.18 and Figure 7.19. The change in period is also evident in the correlation plot (*cf.* Figure 7.19)

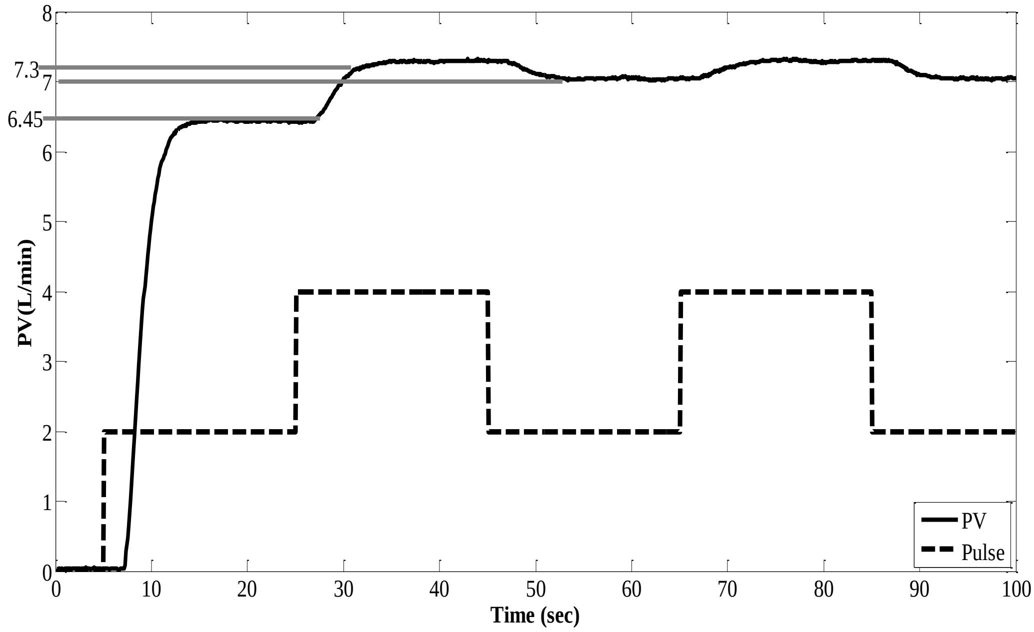


Figure 7.17: Open loop response of plant with simulated hysteresis.

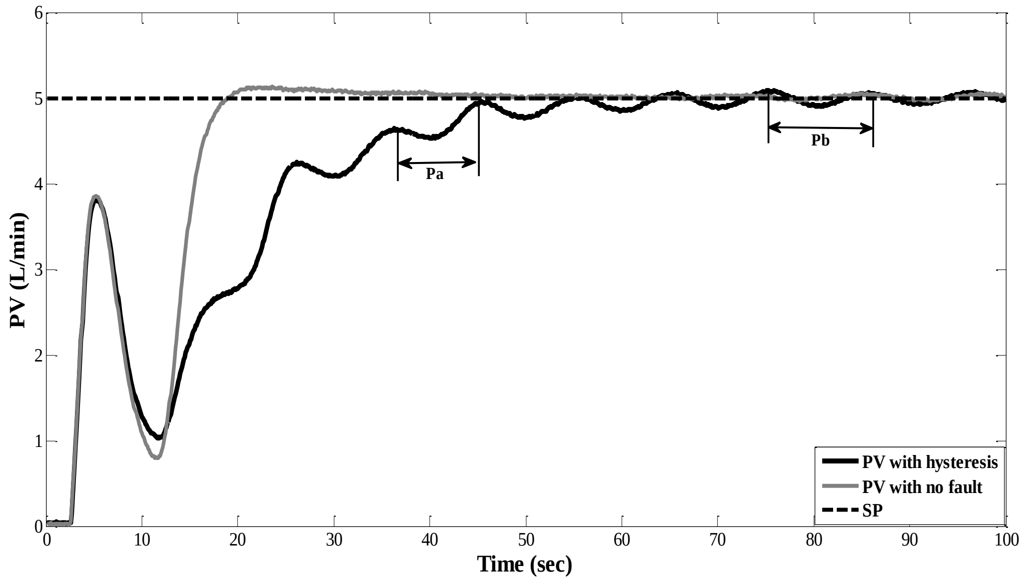


Figure 7.18: Closed loop response of plant with simulated hysteresis.

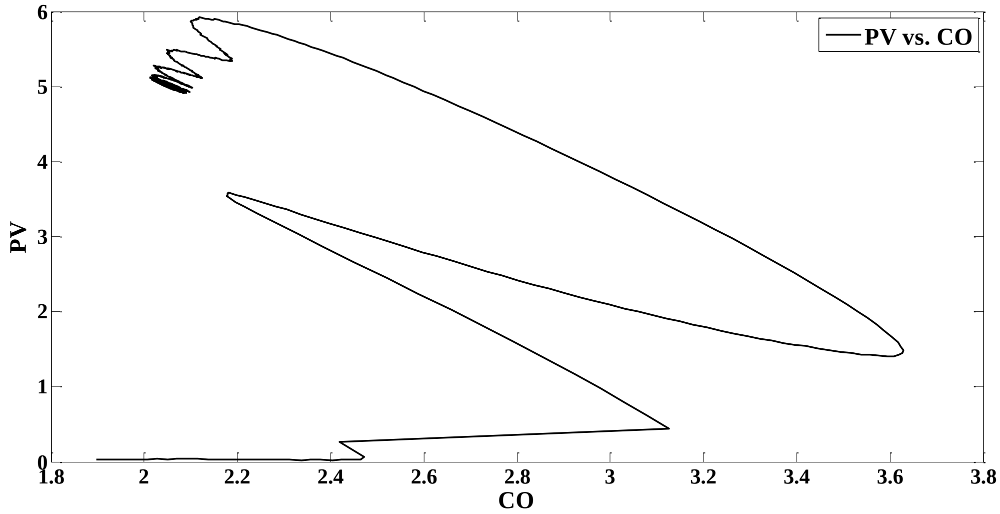


Figure 7.19: Correlation plot of plant with simulated hysteresis.

7.4 SUMMARY AND CONCLUSION

This chapter has proposed two new methods for simulating control valve stiction and control valve hysteresis faults. Typical real-life plant fault conditions such as low air supply and backlash were also simulated and their respective responses were presented. All these faults are to be detected using a system based on an ANN. The following chapter provides the reader with a brief background on ANN's. The reader is referred to the literature for a more detailed discussion on ANN systems and their training methodologies (*cf.* [45], [47], [55], [56]).

This page is intentionally left blank

CHAPTER 8

DEVELOPMENT OF THE ANN ENSEMBLE FAULT DETECTION SYSTEM

8.1 INTRODUCTION

The focus of this research is to develop an ANN based fault detector for typical problems experienced in process control loops. Using a single network to detect these faults would yield satisfactory results. However, following a thorough review of the literature and through experimentation, the author has found that performances of large networks are compromised, especially with regards to computation time and general performance. Following several experiments and comparative studies between single large ANN's and smaller more specialised ANN, the author has concluded that more specialised networks that perform dedicated tasks produce improved results over larger systems. It is for this reason that we have decided to utilise specialised networks, referred to as so called 'ensembles', for our fault detection system. This chapter is divided into PART A, PART B and PART C. Part A discusses the rationale used to design the ANN ensemble; PART B provides a detailed discussion on the Matlab software (version 2010a) that was written to create and train the ANN to behave as an ensemble based fault detection system and PART C discusses the ensemble training results.

PART A: DESIGN OF THE ENSEMBLE ARCHITECTURE

8.2 ANN ENSEMBLES

An ANN ensemble is formed when individual ANNs are trained to solve a complex task by sub-dividing the task and generating a single output [57]. Each ANN develops the ability to perform a single specific sub-task and behaves as a so-called *specialist.* ANN ensembles have the following advantages over a single large ANN network [55]:

1. *Improved robustness*: Ensembles are more tolerant than large networks to noisy data [57].

2. *Improved generalization:* The ensemble is able to estimate with greater accuracy on data that was not seen during the training of the ANNs, therefore a smaller set of training data is required to train an ensemble of ANNs compared to a single ANN [57].

3. *Improved Stability*: The ANN ensembles are not as sensitive to initial parameters as opposed to a single ANN and are more consistent predictors [57] [58].

The architecture of a typical ANN ensemble system is given in Figure 8.1. A more detailed description of the ANN ensemble will be given in the subsequent discussions.

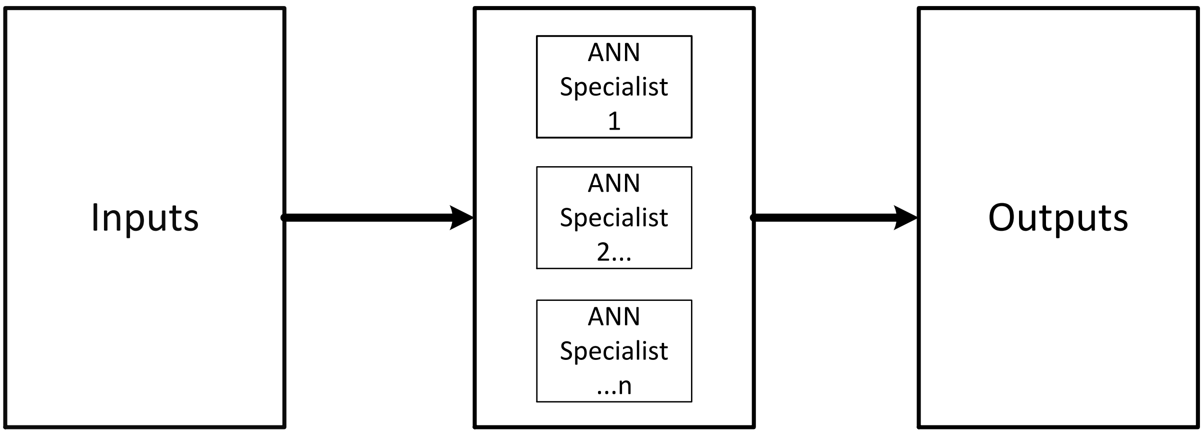


Figure 8.1: ANN ensemble architecture.

8.3 TRAINING AND TEST DATA SETS

ANN's require data for learning how to perform a specific task. Three types of data sets namely *training data*, *test data*, *validation data* and the *target data* sets are required for the design of any ANN system. A brief explanation on how these data sets were created is given in the following discussions. To develop the ANN detector the captured data sets for different loop fault conditions were divided into the following groups:

1. *Training data:* is responsible for updating the network weights and biases.

2. *Validation data*: is used to monitor the training process [59]. The validation data is used to test the network each time the network has been trained throughout the training process and prevents the network from over fitting.

3. *Test data*: is used to test the performance of the trained network. This data is not used during the training process.

4. *Target data*: compromises signatures which exhibited the strongest characteristics for a specific fault. These signatures are selected as target vectors to train the network using the supervised training technique.

Following from the discussions described in *Chapter 7,* twenty-five samples of unprocessed valve signatures corresponding to each considered fault condition was collected. The data array of each fault was then converted from a 1 x 961 vector into a 31 x 31 vector array. Data reshaping was necessary for establishing compatibility when the data was applied to the ANN (*cf.* Figure 8.2).

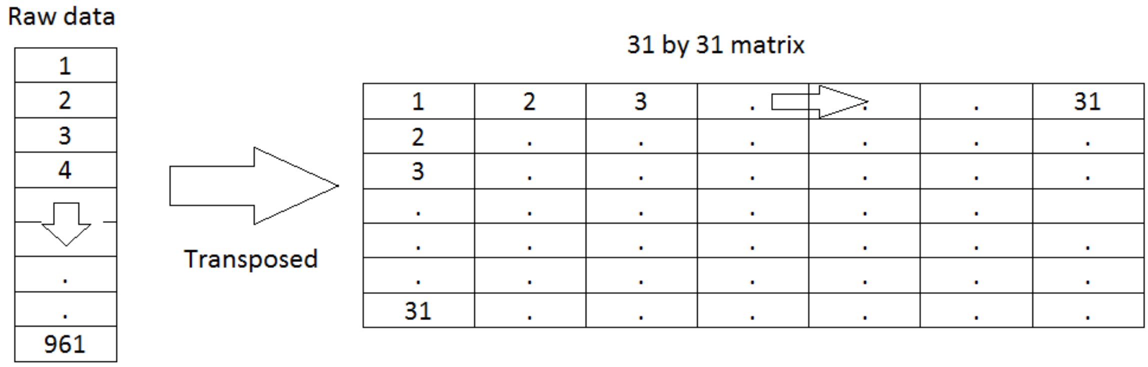


Figure 8.2: 1 x 961 array transposed into 31 x 31 array.

8.4 SELECTION OF ANN ARCHITECTURE AND TRAINING

Feed-forward ANN's were selected for the classifier. Feed-forward ANN's utilising the sigmoidal activation function are regarded as universal classifiers and provide excellent results for multiple classification tasks [55],[60]. With regards to Figure 8.3, the architectural characteristics of the ANN ensemble classifier consists of the following:

- Input Layer
- 1st Hidden Layer (Tan sigmoid)
- 2nd Hidden Layer (Tan sigmoid)
- Output Layer (Linear)

Most literature suggests that one hidden layer in the feed-forward ANN should be sufficient for most tasks [61]. However for this application two hidden layers were chosen so as to accommodate a large range of fault conditions which may have exhibited similar characteristics. The addition of the 2nd hidden layer increased the accuracy but also had the drawback of an increased training time [61]. The tan-sigmoid activation function was selected for the hidden neurons because the classifier has to perform multiple error classification tasks over a range; the log-sigmoid activation function could also be used to

provide similar results. The output of the nonlinear hidden layers is linearized using the linear activation transfer function since the output layer is used for function fitting.

The network was created on an intuitive basis using the 'network growing' technique. The number of hidden layers and neurons per hidden layer was adjusted and trained till optimum results were noted (*cf*. Table 8.1). Input data was fed serially into the ANN and training then commenced using the Leven-Marquart (LM) training algorithm. The LM algorithm is a variant of the back-propagation gradient based training algorithm and provided quick convergence [62]. The ANN is trained for several iterations till the training goal is reached. Upon completion of ANN training, test and validation data was used to test the ANN classifiers performance.

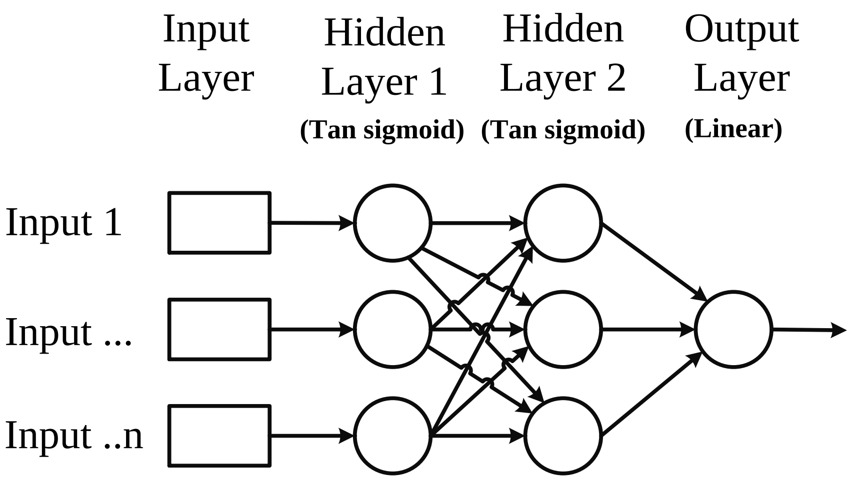


Figure 8.3: Topology of the ANN classifier.

The performance of the NN for conditions corresponding to different loop faults is shown in Table 8.1.With regards to Table 8.1:

i. Data sets [Note 1] P1S22, P1S24 and P1S25 [Note 2] represent valve signatures for the stiction fault for plant 1.
ii. Data sets P1N22 to P1N24 represent normal valve signatures with no fault conditions for plant1.
iii. Data sets P1L21 to P1L24 represent the low air supply fault for plant 1.
iv. Data sets P1B21 to P1B24 represent the backlash fault for plant1.
v. Data sets P1H16 to P1H17 represent the hysteresis fault for plant1.
vi. Data sets P2H1 to P2H3 represent the hysteresis fault for plant 2 [Note 3].
vii. Data sets P3S12 to P3S13 represent the stiction fault for plant 3
viii. Data sets P3B12 to P3B14 represent the backlash fault for plant 3.

Note 1: Example of data sets are shown in Appendix A3

Note 2: Refer to page 10 for definitions to abbreviations.

Note 3: Plant 2 and plant 3 were two additional plants that were used to test the performance of the ANN ensemble fault detector. Refer to Appendix A2 for photos of plants

All data sets used for this comparison were not previously used during the design phase of the network. The best performing networks for each data set input is highlighted in Table 8.1.

		Performance based on the Mean Square Error		
ANN	**Data Set (31 x 31 matrix)**	**10 Neurons per hidden layer**	**20 Neurons per hidden layer**	**31 Neurons per hidden layer**
‘stiction’ ANN (for Plant 1)	P1S22	0.1404	0.2350	0.3352
	P1S24	0.4223	0.5359	0.4715
	P1S25	0.3280	0.4131	0.4622
‘no fault’ ANN (for Plant 1)	P1N22	0.1176	1.0869	0.1984
	P1N23	0.1222	1.0705	0.1408
	P1N24	0.124	1.0660	0.1919
‘low air supply’ ANN (for Plant 1)	P1L21	0.2844	0.1644	0.0151
	P1L22	0.3533	0.3932	0.2843
	P1L23	0.4062	0.2316	0.1934
	P1L24	0.7407	0.3948	1.1795
‘backlash’ ANN (for Plant 1)	P1B21	1.1681	1.0744	1.7344
	P1B22	0.8611	0.8741	0.8601
	P1B23	0.9610	0.8787	1.0231
	P1B24	1.1348	1.0566	1.2468
‘hysteresis’ ANN (for Plant 1)	P1H16[1]	1.8685	0.6721	1.8430
	P1H17	1.8353	0.6889	1.8444
	P1H18	2.1542	0.6298	1.8285
‘hysteresis’ ANN (for Plant 2)	P2H1	2.9607	0.5893	1.1976
	P2H2	2.2319	1.3519	2.3183
	P2H3	1.9443	0.5453	0.9904
‘stiction’ ANN (for Plant 3)	P3S12	0.1333	0.2897	2.1820
	P3S13	0.2503	0.2837	1.8839
	P3S14	0.1940	0.2653	1.9262
‘backlash’ ANN (for Plant 3)	P3B12	42.4241	3.9543	200.0594
	P3B13	26.8391	3.3499	207.1538
	P3B14	38.3789	3.6368	184.4895

Table 8.1: Comparison of ANN performance to vary number of hidden layers.

From Table 8.1 the following ANN architectures were chosen:

Condition	Best performance neurons	ANN
No fault condition (Plant1)	10	P1N10 [Note 1]
Backlash fault (Plant1)	20	P1B20
Low air supply fault (Plant1)	31	P1L31
Stiction Fault (Plant1)	10	P1S10
Hysteresis Fault (Plant1)	20	P1H20
Hysteresis Fault (Plant 2)	20	P2H20
Stiction Fault (Plant 3)	10	P3S10
Backlash Fault (Plant 3)	20	P3B20

Table 8.2: Fault conditions with associated ANN structure.

Note 1: Refer to page 10 for definitions to abbreviations

This page is intentionally left blank

PART B: DISCUSSION ON THE ENSEMBLE (SOFTWARE)

8.5 CONFIGURATION OF THE ENSEMBLE

The ensembles arrangement for identifying loop faults is shown in Figure 8.4. The theory associated with ANN ensembles was discussed in detail in *Chapter 8, Part A section 8.2.* With regards to Figure 8.4, input fault data in the form of a 31 x 31 matrix is fed into each ensemble and the output will be the classification of the control valve fault. For our study we made use of five ANN ensembles. Each ensemble was trained to detect a specific control valve and control loop fault, namely stiction, low air supply, hysteresis, backlash and a 'no fault' condition.

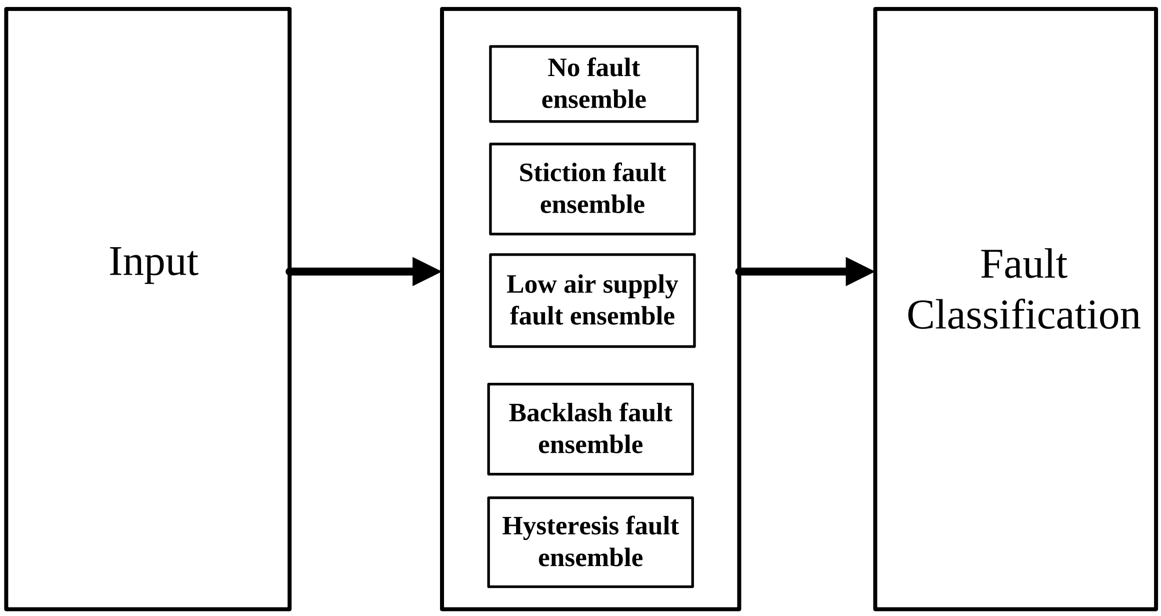


Figure 8.4: Ensemble of ANNs.

The layout of the ensemble is given in Figure 8.5. With regards to Figure 8.5: Input data sets are fed into each of the specialised ANNs and the corresponding *mean squared error* (MSE) performance values are recorded and are used to distinguish between the different fault conditions. A comparison between the MSE of each ensemble is then made. The ensemble with the lowest MSE is chosen as the detector of a specific fault. The low MSE indicates that the ensemble network has been specifically trained to detect only a certain fault. The flowchart describing the rationale followed to design the proposed fault detection software is given in Figure 8.6. With regards to the flowchart shown in Figure 8.6:

The test sample is fed into each of the 8 specialised ANNs and the corresponding MSE performance values are recorded. These MSE performance values are compared to each other and the ANN specialist with the best performance (closest value to zero) is used to classify the fault condition.

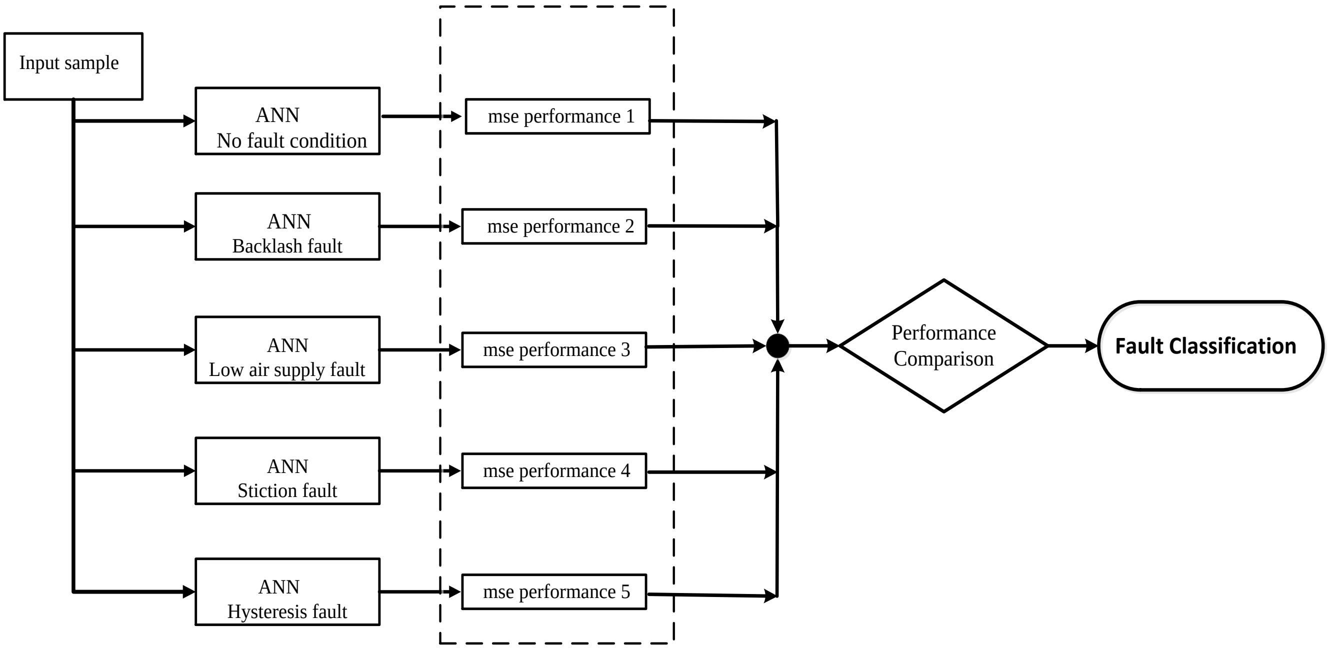


Figure 8.5: Flow diagram of ensemble system.

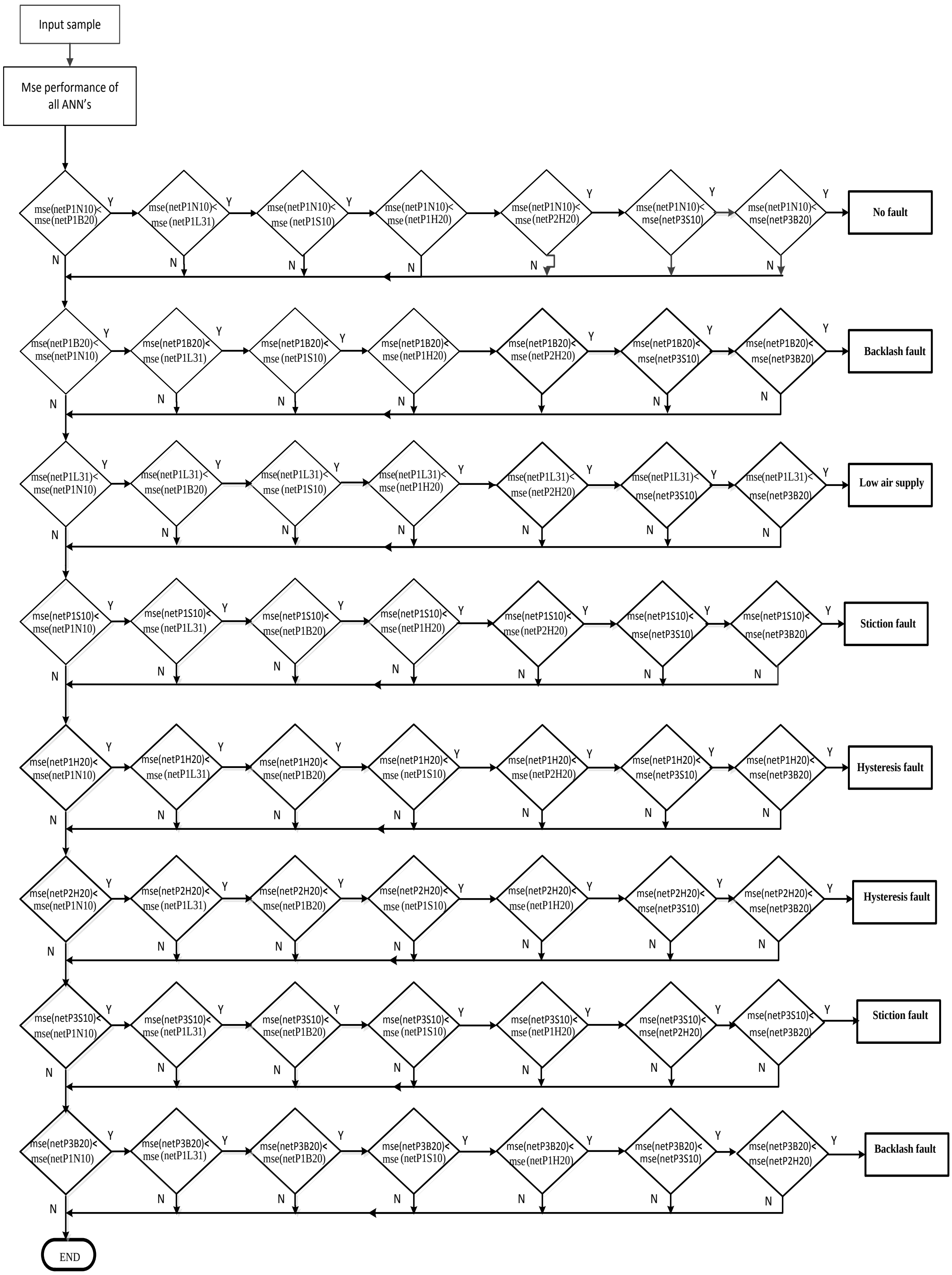


Figure 8.6: Flow chart for the fault detecting ensemble system.

The equations describing how each ensemble detects a dedicated fault are given in equations 8.1 to equation 8.8. The acronyms used in equations 8.1 to equation 8.8 are defined in Table 8.2.

$$MSE\ of\ P1N10 < \begin{cases} MSE\ of\ P1L31 \\ MSE\ of\ P1B20 \\ MSE\ of\ P1H20 \\ MSE\ of\ P1S10 \\ MSE\ of\ P2H20 \\ MSE\ of\ P3S10 \\ MSE\ of\ P3B20 \end{cases}$$ (Equation 8.1: No fault condition)

$$MSE\ of\ P1B20 < \begin{cases} MSE\ of\ P1L31 \\ MSE\ of\ P1B20 \\ MSE\ of\ P1H20 \\ MSE\ of\ P1S10 \\ MSE\ of\ P2H20 \\ MSE\ of\ P3S10 \\ MSE\ of\ P1N10 \end{cases}$$ (Equation 8.2: backlash fault condition)

$$MSE\ of\ P1L31 < \begin{cases} MSE\ of\ P1N10 \\ MSE\ of\ P1B20 \\ MSE\ of\ P1H20 \\ MSE\ of\ P1S10 \\ MSE\ of\ P2H20 \\ MSE\ of\ P3S10 \\ MSE\ of\ P3B20 \end{cases}$$ (Equation 8.3: low air supply condition)

$$MSE\ of\ P1S10 < \begin{cases} MSE\ of\ P1L31 \\ MSE\ of\ P1B20 \\ MSE\ of\ P1H20 \\ MSE\ of\ P1N10 \\ MSE\ of\ P2H20 \\ MSE\ of\ P3S10 \\ MSE\ of\ P3B20 \end{cases}$$ (Equation 8.4: stiction fault condition)

$$MSE\ of\ P1H20 < \begin{cases} MSE\ of\ P1L31 \\ MSE\ of\ P1B20 \\ MSE\ of\ P1S10 \\ MSE\ of\ P1N10 \\ MSE\ of\ P2H20 \\ MSE\ of\ P3S10 \\ MSE\ of\ P3B20 \end{cases}$$ (Equation 8.5: hysteresis fault condition)

$$MSE\ of\ P2H20 < \begin{cases} MSE\ of\ P1L31 \\ MSE\ of\ P1B20 \\ MSE\ of\ P1S10 \\ MSE\ of\ P1N10 \\ MSE\ of\ P1H20 \\ MSE\ of\ P3S10 \\ MSE\ of\ P3B20 \end{cases}$$ (Equation 8.6: hysteresis fault condition)

$$MSE\ of\ P3S10 < \begin{cases} MSE\ of\ P1L31 \\ MSE\ of\ P1B20 \\ MSE\ of\ P1S10 \\ MSE\ of\ P1N10 \\ MSE\ of\ P1H20 \\ MSE\ of\ P2H20 \\ MSE\ of\ P3B20 \end{cases}$$ (Equation 8.7: stiction fault condition)

$$MSE\ of\ P3B20 < \begin{cases} MSE\ of\ P1L31 \\ MSE\ of\ P1B20 \\ MSE\ of\ P1S10 \\ MSE\ of\ P1N10 \\ MSE\ of\ P1H20 \\ MSE\ of\ P2H20 \\ MSE\ of\ P3S10 \end{cases}$$ (Equation 8.8: backlash fault condition)

The performance of the fault detecting ensemble is shown in Table 8.3. The ANN exhibiting the best performance produces the smallest MSE and is an indication of the fault classification. The best performing ensembles are highlighted in Tables 8.3.

Performance (MSE)								
Data Set	**netP1N10**	**netP1B20**	**netP1L31**	**netP1S10**	**netP1H20**	**netP2H20**	**netP3S10**	**netP3B20**
P1N22	0.1176	2.2632	1.1211	8.5317	1.2422	0.9748	367.4087	2.2878e^{3}
P1N23	0.1222	2.3423	1.1931	8.6171	1.2293	0.9374	367.5223	2.2880e^{3}
P1N24	0.1241	2.4576	1.2091	8.8381	1.2742	0.9681	367.3100	2.2875e^{3}
P1B22	3.4536	0.8741	3.3971	11.4211	4.8135	1.6561	394.4886	2.4180e^{3}
P1B23	3.5496	0.8787	4.0059	11.3947	4.9244	1.4574	398.0337	2.4230e^{3}
P1B24	3.9556	1.0566	5.3147	11.3923	5.5166	1.8030	398.6428	2.4206e^{3}
P1L21	0.8920	0.9228	0.0151	6.9089	1.4078	1.1228	374.3071	2.3170 e^{3}
P1L22	0.9744	0.8367	0.2843	6.2706	1.0788	0.8870	373.1188	2.3176e^{3}
P1L23	0.8613	1.0365	0.1934	6.7714	0.9167	1.2045	374.1731	2.3268e^{3}
P1S22	14.1180	5.6368	17.4239	0.1404	14.2233	10.4191	359.4892	2.1456e^{3}
P1S24	15.5027	5.9604	19.6797	0.4223	14.4217	10.3277	362.4205	2.1572e^{3}
P1S25	15.9275	5.9604	19.6797	0.3280	14.4217	10.3277	362.4205	2.1572e^{3}
P1H16	0.7041	2.5131	1.9756	9.1323	0.6721	2.8044	358.4564	2.2432e^{3}
P1H17	0.7070	2.3612	1.9516	9.3450	0.6889	2.8719	358.3414	2.2426e^{3}
P1H18	0.7647	2.5908	2.1462	9.0273	0.6298	2.9292	358.4534	2.2410e^{3}
P2H1	3.6301	2.7125	15.7781	11.4141	3.0062	0.5893	385.1027	2.3609e^{3}
P2H2	3.5121	2.7173	7.4664	11.5943	3.3882	1.3519	392.8826	2.3738e^{3}
P2H3	1.0530	6.1039	4.6497	8.9597	1.1730	0.5453	375.4599	2.3221e^{3}
P2L1	1.5798	1.1986	5.9302	11.1670	3.1368	2.3439	399.4912	2.4386e^{3}
P2L2	1.9528	1.5556	6.5559	9.4247	3.4017	2.4127	399.4560	2.4266e^{3}
P2L3	1.8957	1.8924	4.1394	10.4122	3.1368	2.3748	398.2585	2.4369e^{3}
P3S12	166.8827	40.7225	13.4876	32.4405	14.6229	25.6937	0.1333	96.9260
P3S13	166.8539	42.8902	13.4814	32.4312	14.4116	25.6645	0.2503	95.0588
P3S14	166.8650	42.4731	13.4837	32.4365	14.5183	25.6767	0.1940	95.1745
P3B12	167.5097	54.4770	18.9949	32.5187	7.9227	26.6349	112.4572	3.9543
P3B13	167.5442	45.0032	18.7795	32.5250	7.8746	26.5816	112.4643	3.3499
P3B14	167.4202	52.0032	19.7091	32.4950	7.7927	26.5881	112.2888	3.6368

Table 8.3: Comparison of each ANN's (MSE) performance (the highlights represent the MSE of the best performing neurons).

This page is intentionally left blank

PART C: ENSEMBLE PERFORMANCE PLOTS

This section of the study discusses the training results for our ensemble based diagnostics system. A discussion of the *training data-set, target data-set, validation data-set and test data-set* was given in PART A of Chapter 8.

The supervised learning method was used to train each ANN ensemble for the proposed diagnostic system. The signatures which exhibited the strongest characteristics for a specific fault were selected as target vectors to train the network. The training data set is fed serially into the ANN during each iteration (an application of the data into the network for learning). The network was trained using the Leven-Marquart backpropagation learning algorithm, which monitored the gradient of the ANN's performance functions and adjusted the ANN's free parameters as the network learned to recognise the target vector. With each iteration of input data the ANN converges towards the performance goal. The MSE performance function was used to evaluate network performance. For a properly designed network, with appropriate data the MSE will approach a minimal value as the network learns. In certain instances the performance converges at a local minimum which is far from the global goal. This early convergence can be attributed to the saturation of the network's free parameters, or a lack of momentum during transitions of the network's weights and biases. A more detailed analysis of the training results can be found in chapter 9.

The following parameters were set for each of the networks prior to training:

- Maximum Epochs: 1000
- Goal: 1.00 x 10^{-7}
- Minimum gradient: 1.00 x 10^{-10}
- Maximum validation failures: 6

These parameters were empirically decided upon and were found to produce the best results. The training of the network will stop when any of the above conditions occur.

C1. Ensemble for the stiction fault condition, plant 1 (*cf*. Figure 8.7)

The ANN performance plot in Figure 8.7 outlines the training, validation, and test performances. The training, test and validation plots follow a similar trajectory. This indicates that no major problems occurred while training the network. The validation test set reached a minimum global minimum value of 0.086658 at the 8th iteration.

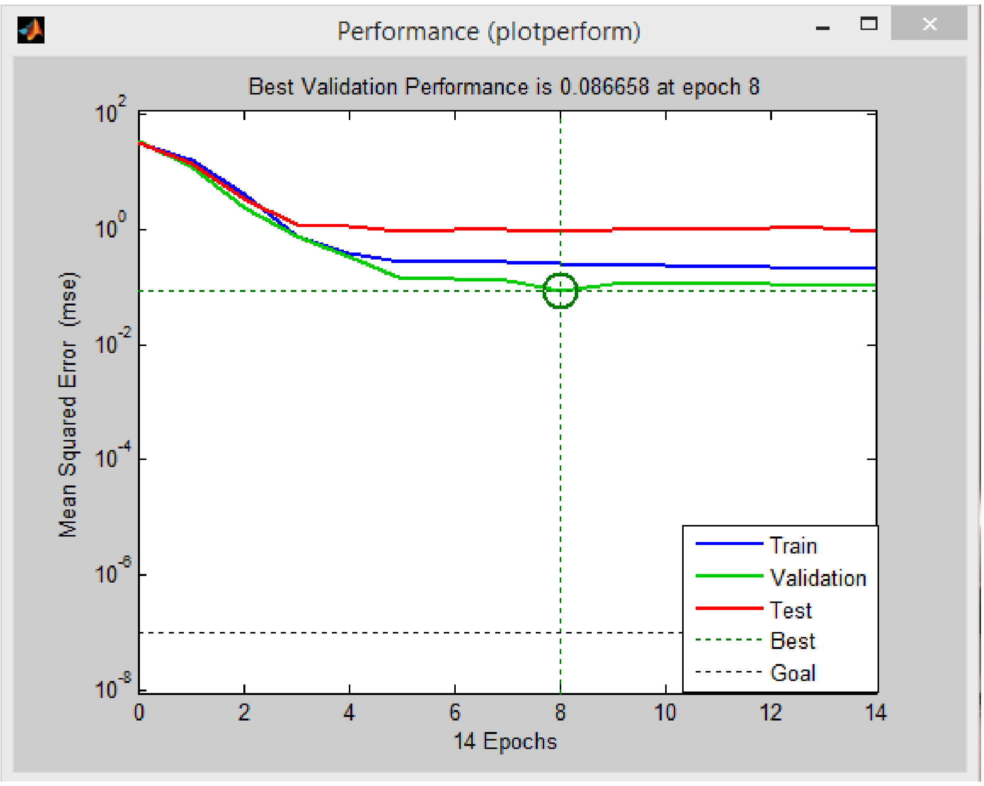


Figure 8.7: Performance plot of stiction ANN for plant 1 (netP1S10).

C2. Ensemble for no fault condition, plant 1 (*cf.* Figure 8.8)

The rate of change of the training and validation sets reduced after the 2nd iteration and thereafter gradually decreased towards the minimum. This rate change is due to the fact that the error magnitude is largest at the beginning of training. The rate at which the changes occur will reduce as the error moves closer to the goal. Both training and validation sets follow a similar path until the 6th iteration and the best performance was reached at the 7th iteration. The local minimum performance of 0.20144 is achieved after 7 iterations. The test and validation set stabilizes after the 8th iteration and training stops after 12 iterations.

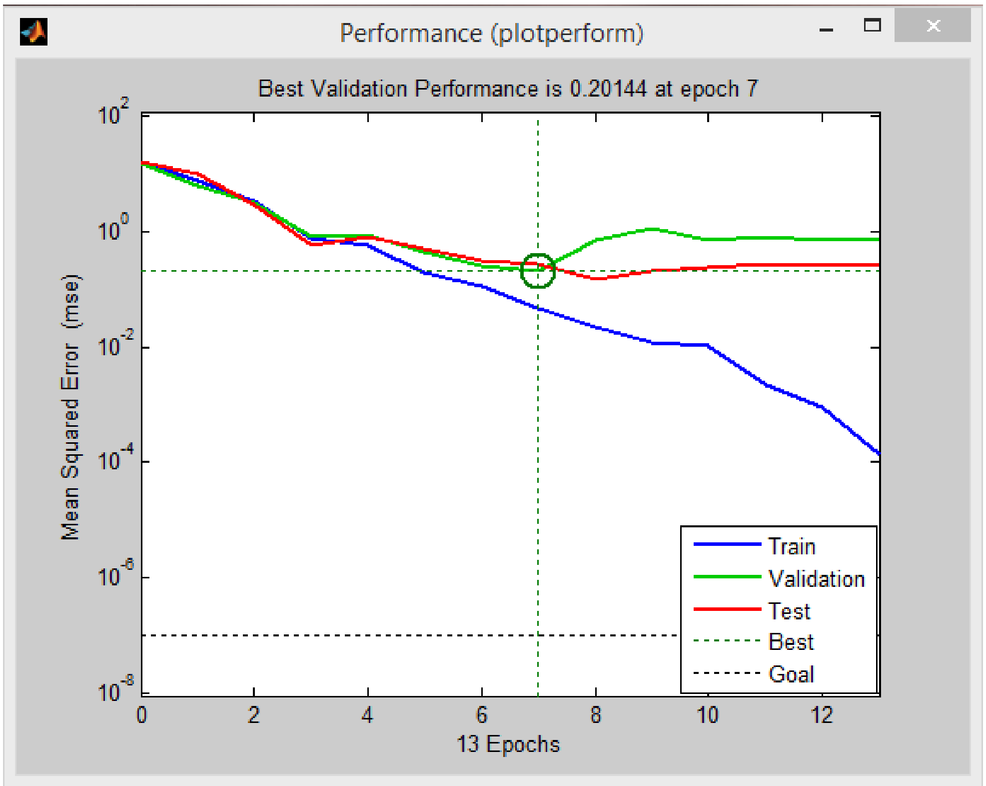


Figure 8.8: Performance plot of ANN with no fault condition for plant 1 (netP1N10).

C3. ANN for the low air supply fault condition, plant 1 (*cf*. Figure 8.9)

The training error gradually reduced with training until the 46th iteration where the best performance validation of 0.43294 was reached. The performance stabilizes and training continues for a further 4 iterations before coming to a stop.

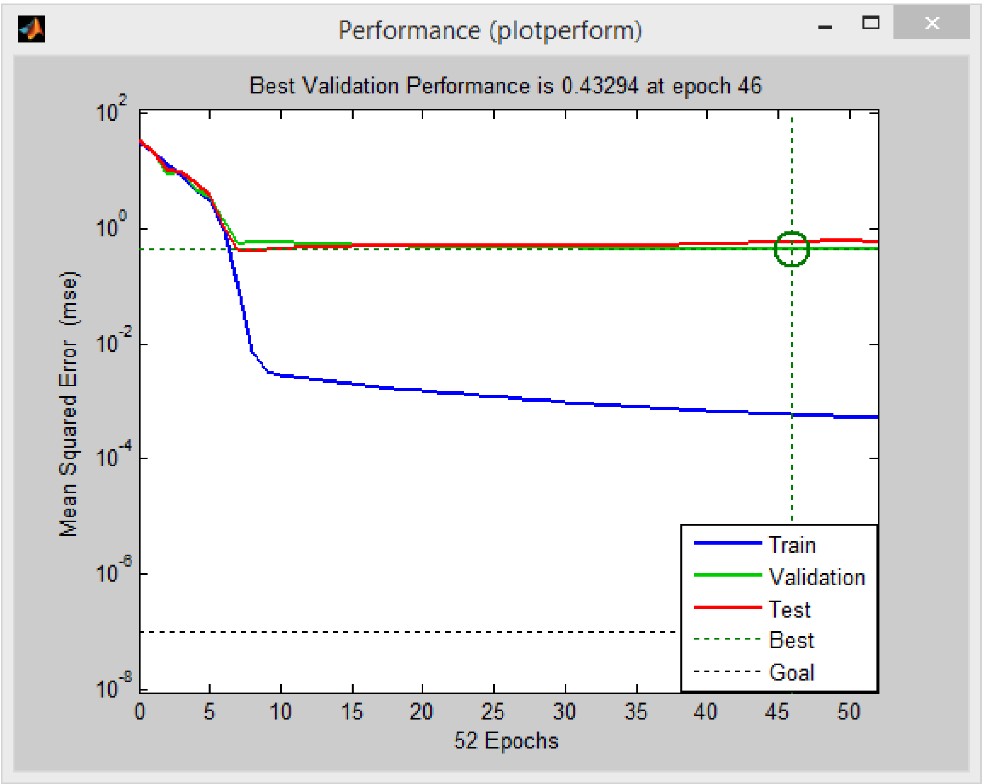


Figure 8.9: Performance plot of low air supply ANN for plant 1 (netP1L31).

C4. ANN for the backlash fault condition, plant 1 (*cf.* Figure 8.10)

Figure 8.10 indicates the training process of the ANN used to classify the backlash fault condition. All three sets converged towards the minimum performance until the best validation performance of 0.199 was reached at epoch 5. Training continues and stops once global convergence is reached.

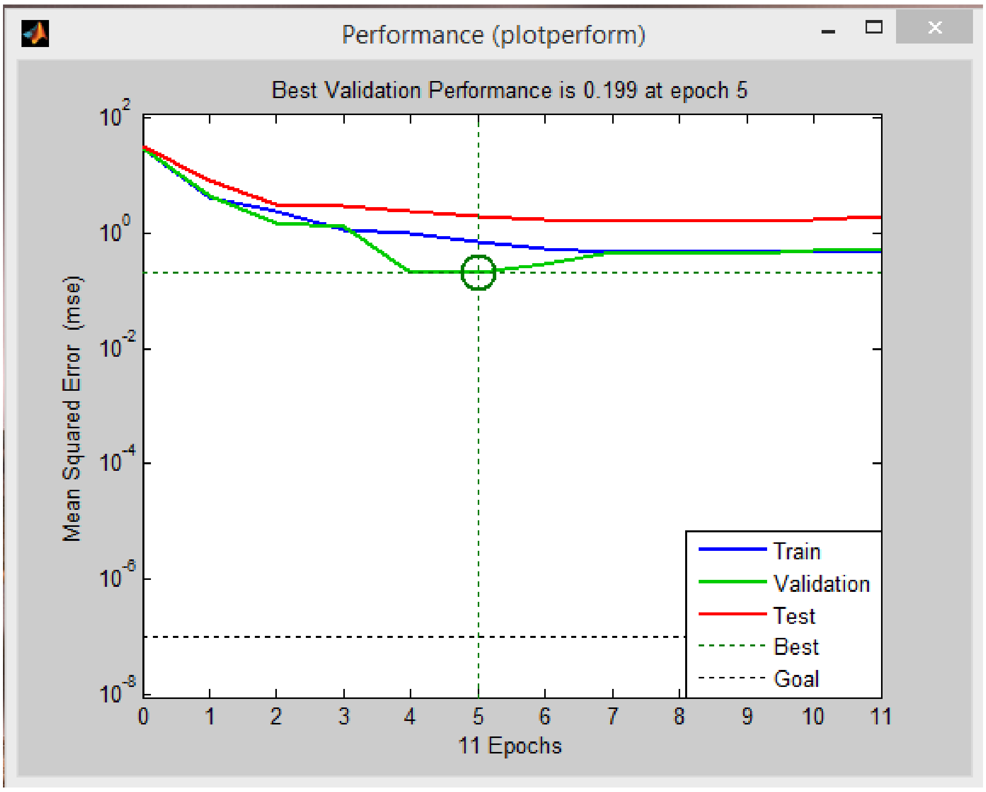


Figure 8.10: Performance plot of the backlash ANN for plant 1 (netP1B20).

C5. ANN for the hysteresis fault condition, plant 1 (*cf.* Figure 8.11)

Initially the rate of change of the training, validation and test sets was minimal, until the update of the network's weights and biases during the training caused the rate of error to increase. All three sets initially decreased until the 6th iteration, thereafter stabilizing. The best performance validation of 0.0031122 is reached after 9 iterations and training continues until the 15 iteration.

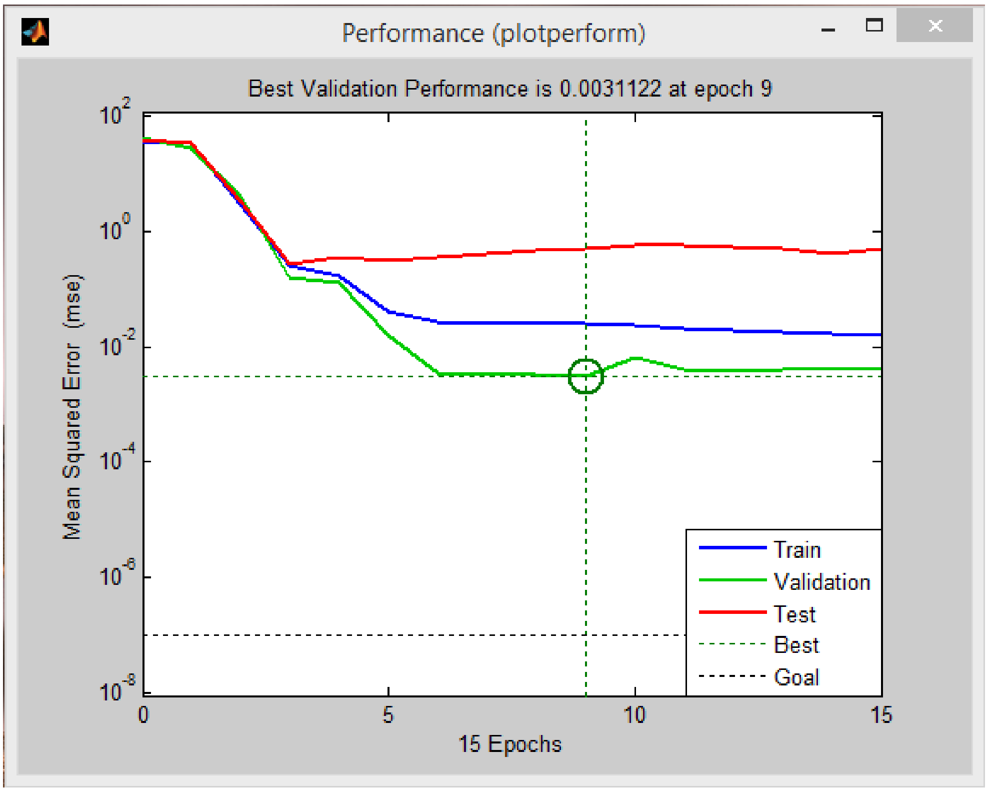


Figure 8.11: Performance plot of the hysteresis ANN for plant 1(netP1H20).

C6. ANN for the hysteresis fault condition, plant 2 (*cf.* Figure 8.12)

Figures 8.12 outlines the training of the ANNs used to classify the hysteresis fault condition from plant 2. All three data sets decreased as the network trained. The best validation performance of 0.29933 was reached after 6 iterations, training stopped after 12 iterations when the minimum gradient was reached.

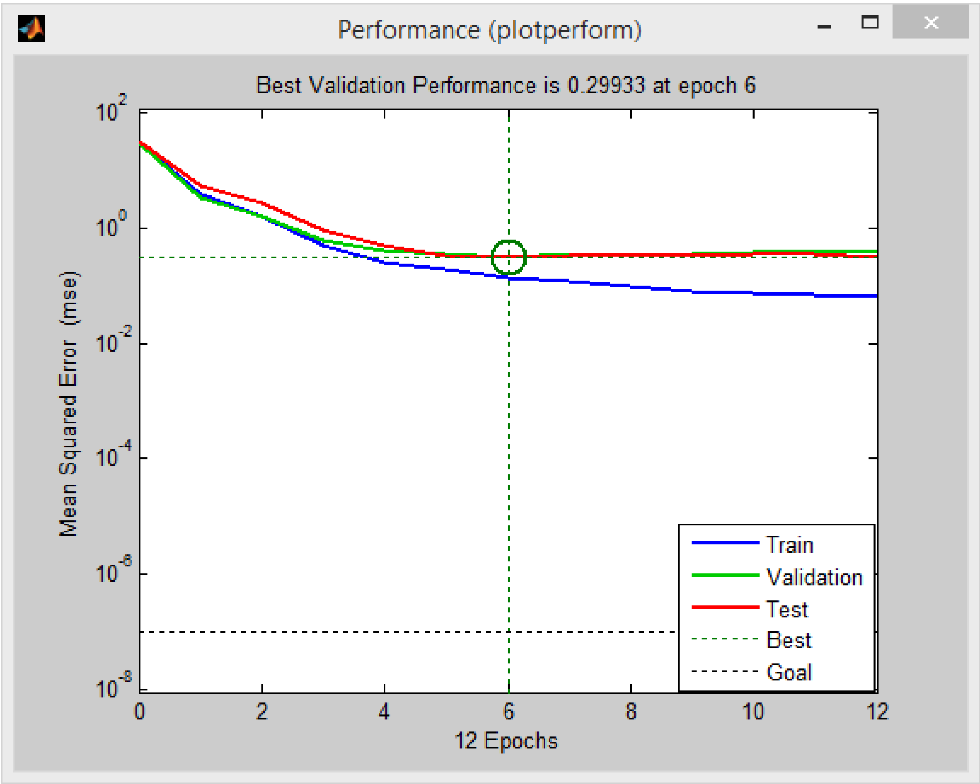


Figure 8.12: Performance plot of the Hysteresis ANN for plant 2 (netP2H20).

C7. ANN for the Stiction fault condition, plant 3 (*cf*. Figure 8.13)

The ANN performance plot in Figure 8.13 outlines the training, validation, and test performances. The training, test and validation plots followed a similar downward trajectory; this indicates no major problems occurred during training of the network. The validation test set reached minimum of 0.28259 after the 7 iterations.

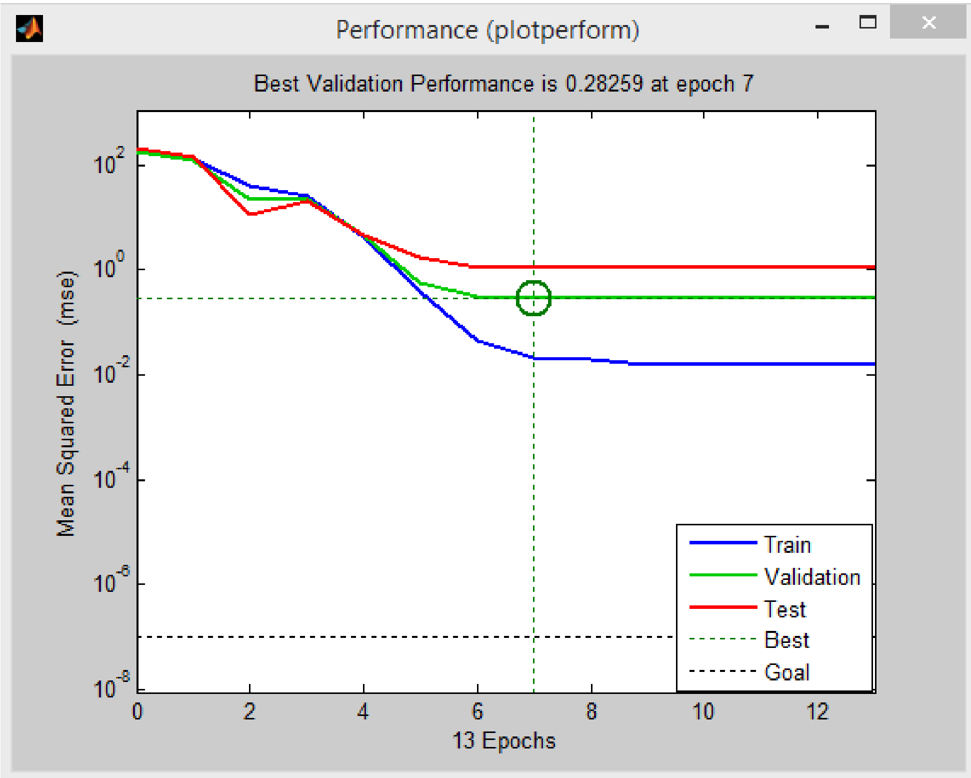


Figure 8.13: Performance plot of the Stiction ANN for plant 3 (netP3S10).

C8. ANN for the Backlash fault condition, plant 3 (*cf.* Figure 8.14)

Figures 8.14 outlines the training of the ANNs used to classify the backlash fault condition from plant 3. As the weights are updated following each iteration, the network error decreases until the minimum performance of 0.12097 is reached after the 10th iteration. Training continues for a further 6 iterations with no decrease in error and training ends after 16 iterations.

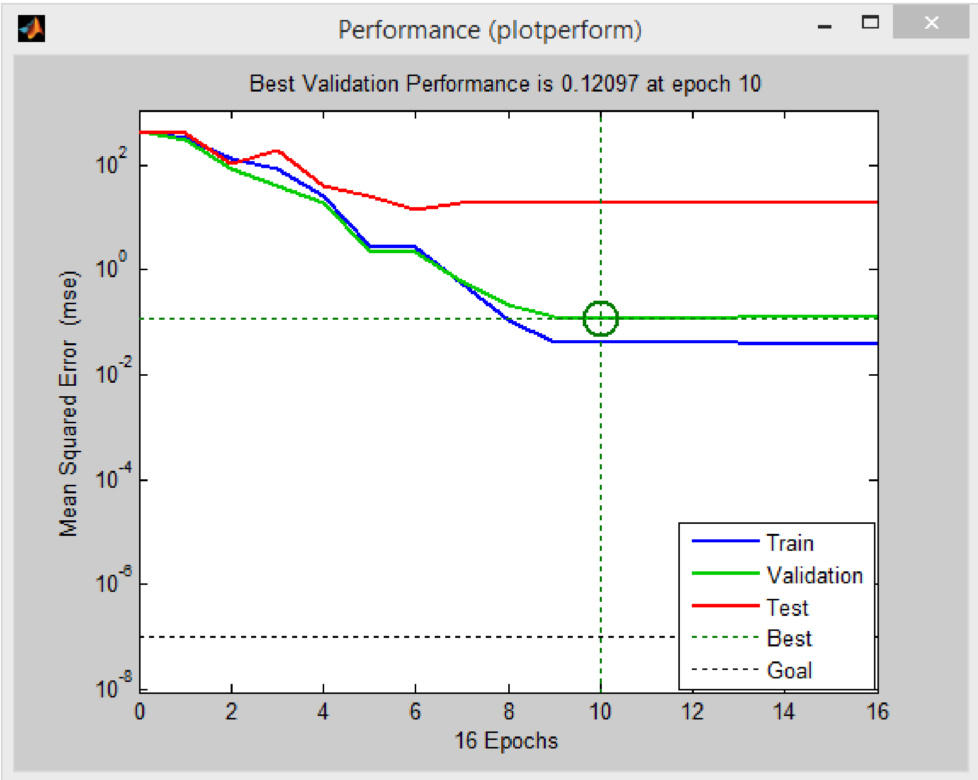


Figure 8.14: Performance plot of the backlash ANN for plant 3 (netP3B20).

8.5 SUMMARY AND CONCLUSION

This chapter discussed the architecture of the ANN ensemble and also described the rationale followed to develop the software for the loop fault detection system. The network training responses were also presented and brief discussions were provided for each response. The following chapter will provide a detailed analysis of the training results presented in this chapter.

This page is intentionally left blank

CHAPTER 9

ANALYSIS OF TRAINING RESULTS

9.1 INTRODUCTION

The procedure followed to design and train the ensemble was presented in the previous chapter. The training results were also shown. This chapter will focus on the analysis of the results that were presented in Chapter 8.

9.2 PROBLEM OF LOCAL MINIMUM

One of the major disadvantages of using the back propagation learning algorithm is the possibility of the learning process terminating prematurely at a *local minimum*, which may be far from the global minimum goal [63]. This is evident in the performance plots (*cf.* Figures 8.7 to Figure 8.14), where the training of each ANN stops at the local minimum when the minimum gradient was reached. The network reached a global minimum when any one of the user specified early stopping criteria was reached. Training beyond the global minimum will lead to overtraining, and will cause the network to overshoot the goal, that is train beyond the required criteria.

The network converges in a local minimum (*cf.* Figure 9.1) when the error falls and is unable to rise or fall any further. This convergence is due to the network's free parameters (weights and biases) becoming saturated (not updating) when the minimum gradient is reached during backpropagation training [64]. When neurons reach saturation they become less sensitive to further inputs and this inhibits learning [64].

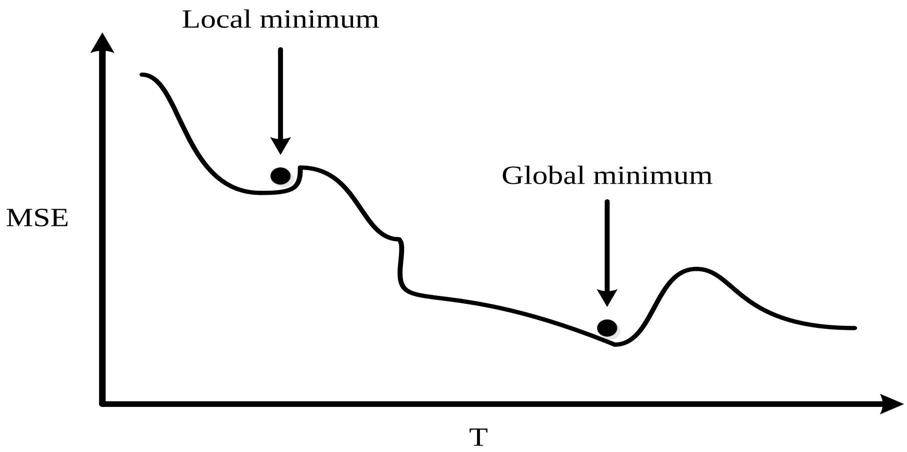


Figure 9.1: ANN error performance plot [64].

A local minimum can be overcome by using combinations of the following solutions

- The addition of the momentum factor influences the updating of the network weights following a training iteration. This could prevent the error from converging into a local minimum [45].
- By adjusting the learning rate, the speed of the ANN's convergence is affected. This may prevent convergence into the local minima.
- Increasing the size of the hidden layer may reduce the possibility of weight saturation. This is because an increased number of neurons will contribute towards the network reaching the goal without substantial adjustments to a neuron's free parameters.

- The adjusting of the initial weights affects the final solution and rate of ANN convergence. Selecting random initial weights may prevent convergence into a local minima.

- Annealing is a natural process which occurs when metals are melted and gradually cooled until the solid state is reached. The process reaches the lowest energy state naturally [65]. An annealing algorithm models the transition of the metal from a high temperature (melting point) to thermal equilibrium [65]. The annealing method is a global search technique and may be used to overcome the disadvantages of the back-propagation algorithm by adjusting updating the free parameters till a state of equilibrium is reached at the global minimum.

9.3 REASONS FOR CONVERGENCE AWAY FROM THE ERROR GOAL

The training of each of the NNs was based on quantitative data rather than qualitative data. We utilised large unprocessed data sets corresponding to each fault condition for training each ANN in the proposed diagnostics system. This large unprocessed data sets contained redundant components which could be a contributing factor to the partially sub-optimal network performance. However this sub-optimal performance does not necessarily affect the classification capacity of an ANN because they are fault tolerant.

We could have achieved a better performance by appropriate pre-processing of the input data for selecting only the salient vectors corresponding to each fault. These smaller data sets of pertinent vectors would improve network performance [66].

PCA is an effective pre-processing technique used across many research fields to extract the non-redundant data vectors from large complex data sets. By reducing the size and complexity of data sets, the ANN computational time would be reduced to yield a better performance.

9.4 CONTROL VALVE FAULT SIGNATURES

Data corresponding to the flow rate was used to develop control valve fault signatures. These flow signatures formed the training, testing and validation data sets for the ensemble. Each of the developed fault detecting ensembles was unique in the sense that an ensemble that worked for Plant 1 did not correctly classify faults on the other two plants. The reason for this is as follows:

An ensemble which produces satisfactory results on one specific plant that it was trained for will not reproduce similar results when tested on another plant. This is because control loops contain different loop elements (such as transmitters, pipes length and diameter, fluid density, control valves), with each element having its own unique signature. Given these reasons, it was necessary to retrain our ensemble with data from each new plant in order for correct classification to take place.

From the above-mentioned discussions, it therefore became necessary for us to design three different ensemble sets for classifying faults on three different process plants (*cf.* Figure 9.2)

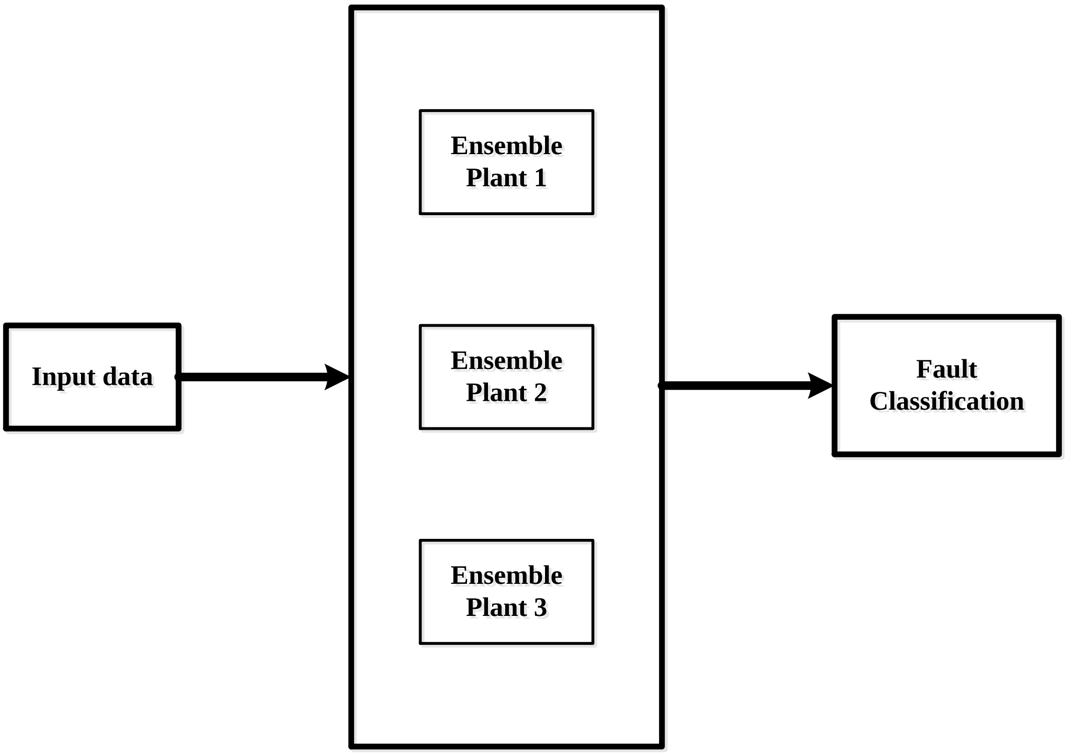


Figure 9.2: Ensemble of ANNs for all three process plants.

The diagnostic ensemble system was tested with data sets of fault conditions which were not used during the training of the ANNs. All data sets were correctly classified as shown in Table 9.1. This table can be verified against Table 8.3.

Condition of Data Set	Data Set	Fault Classification
No fault condition (Plant1)	P1N22	No fault
	P1N23	No fault
	P1N24	No fault
Backlash fault (Plant1)	P1B22	Backlash fault
	P1B23	Backlash fault
	P1B24	Backlash fault
Low air supply fault (Plant1)	P1L21	Low air supply fault
	P1L22	Low air supply fault
	P1L23	Low air supply fault
Stiction fault (Plant1)	P1S22	Stiction fault
	P1S24	Stiction fault
	P1S25	Stiction fault
Hysteresis fault (Plant1)	P1H16	Hysteresis fault
	P1H17	Hysteresis fault
	P1H18	Hysteresis fault
Hysteresis fault (Plant 2)	P2H1	Hysteresis fault
	P2H2	Hysteresis fault
	P2H3	Hysteresis fault
Low air supply fault (Plant 2)	P2L1	Low air supply fault
	P2L2	Low air supply fault
	P2L3	Low air supply fault
Stiction fault (Plant 3)	P3S12	Stiction fault
	P3S13	Stiction fault
	P3S14	Stiction fault
Backlash fault (Plant 3)	P3B12	Backlash fault
	P3B13	Backlash fault
	P3B14	Backlash fault

Table 9.1: Results of diagnostic system.

9.5 SUMMARY AND CONCLUSION

A detailed analysis of the ANN training results indicated instances when the ANNs performance converged at a local minimum instead of a global minimum. This early convergences is a disadvantage of using the back propagation training algorithm. A detailed discussion of this problem of ‘local minima’, with several possibly solutions was presented in this chapter.

The analysis of the ANN training results also indicated, partially sub-optimal network performances, where the ANNs performance convergences away from the error goal. The contributing factors to this problem with possible solutions were presented in this chapter. It must be noted that the ANNs fault tolerant characteristics negated the sub-optimal network performance. This chapter also discussed the reasoning for using three different ensemble sets for classifying faults from three different process plants. The following chapter summarises and concludes this research.

This page is intentionally left blank

CHAPTER 10

SUMMARY, CONCLUSION AND FUTURE WORK

This research proposed the design and development of an ANN ensemble based diagnostic system to monitor the health of process control valves. Control loop signatures of specific fault conditions were extracted from a mini plant during control sessions. The proposed nonintrusive diagnostics system required signatures of typical control loop faults such as control valve stiction, hysteresis, backlash and low air supply. These fault signatures were used to train the ANN to identify specific control valve fault conditions. The loop faults were successfully simulated on a mini plant as follows:

1. Backlash: The Matlab backlash Simulink block model was used to simulate the backlash fault condition.
2. Low Air Supply: The low air supply fault condition was simulated by reducing the amount of air flow to the control valve actuator.
3. Hysteresis: A new Matlab Simulink model was created to simulate the hysteresis fault.
4. Stiction: A new method to simulate stiction in control valves was developed. The operating characteristic of the valve was altered by modifying the CAM on the valve positioner to simulate stiction.

The two new proposed techniques to simulate control valve stiction and hysteresis eliminate the need to create complex models for closed-loop stability analysis and the investigation of compensation methods under dynamical conditions. A more detailed discussion on the development of these fault conditions can be found in Chapter 7 and in the attached published proceedings.

A stickband compensator was also developed and applied to the plant for reducing stickband and limit cycle amplitude. The proposed method was based on Glattfelder's and Schauffelberger's technique where 'anti-windup jacket' was used to reduce the effect of nonlinearity on a control loop [14].

Following extensive research and testing, the feedforward ANN's architecture with the backpropagation training algorithm was found to be the best suited for this research. Each ANN was created using the 'network growing' technique, where the number of hidden layers and neurons per hidden layer was adjusted and trained till optimum results were found. A more detailed discussion on the architecture of the ANN used for the fault classification is given in Chapter 8.

The idea of utilising ensemble architecture for our fault detection system was adopted because we found that an ensemble enhanced the ANNs generalisation ability, hence improving the classifying capability of a network [57]. Input data sets were fed into each of the specialised ANNs, and each 'specialist' provided the corresponding MSE performance values for the same input data set. A program was then developed to compare the MSE performance values for each ANN 'specialist'. The results of the comparison, was then used to distinguish between the different fault conditions.

ANN performance plots highlighted the main drawback of the back propagation learning algorithm, where ANN learning ceased at a local minimum instead of a global minimum. Several possibly solutions to the problem of 'local minimum' were outlined in Chapter 8. However, in spite of early convergence, the ensembles still performed their classification tasks for the plants that were trained for. This can be attributed to the excellent fault tolerance and generalisation capacity of artificial neural networks.

The study was successful and the objectives were achieved. The results of this work were presented at two international conferences and the complete papers were published in the proceeding. The papers are given in the appendix. The author is currently writing a journal paper of this work.

Future work in the field of AI and process control loops will utilize an artificial immune algorithm to detect loop faults, and to a limited extent, to perform corrections when these faults occur.

This page is intentionally left blank

REFERENCES

[1] B. Huang, "Bayesian methods for control loop monitoring and diagnosis," *Journal of Process Control*, vol. 18, pp. 829-838, October 2008.

[2] Control Engineering Asia, "Control valve diagnostics", 2006. [Online]. Available: http: //www.ceasiamag.com/2006/08/control-valve-diagnostics/. [Accessed: 30-Nov-2015].

[3] L. Mann *et al*, "Statistical-based or condition-based preventive maintenance?", *Journal of Quality in Maintenance Engineering*, vol. 1, pp. 46-59, February 1995.

[4] W. Boyes. "Ten Steps to Avoid Unnecessary Plant Shutdowns – Documents", Docslide.us,2014. [Online]. Available: http://docslide.us/documents/tent-steps-to-avoid-unnecesary-plant-shutdowns.html. [Accessed: 30-Nov-2015]

[5] P. Gruhn, "Benefits of valve signature and partial stroke testing", *INTECH*, vol. 50, pp. 53-53, January 2003.

[6] G. Birchfield, "Olefin Plant Reliabilty", 2015, [Online]. Available:http://www.aspentech.com/publication_files/olefinsreliability.pdf. [Accessed: 30- Nov- 2015].

[7] N. Rinehart, "Rethink your control valve maintenance", *Chemical Processing*, 2015. [Online]. Available: http://www.chemicalprocessing.com/articles/2006/045/. [Accessed: 30- Nov- 2015].

[8] S. Alcozer *et al*, "Using higher order CMAC to improve the performance of control valves," *ISA Transactions*, vol. 36, pp. 65-70, 1997.

[9] S. Wang and Z. Jiang, "Valve fault detection and diagnosis based on CMAC neural networks," *Energy & Buildings*, vol. 36, pp. 599 - 610, 2004.

[10] H. Zabiri and M Ramasamy, "NLPCA as a diagnostic tool for control valve stiction," *Journal of Process Control*, vol. 19, pp. 1368 - 1376, 2009.

[11] Y. Yamashita, "An automatic method for detection of valve stiction in process control loops," *Control Engineering Practice*, vol. 14, pp. 503-510, 2006.

[12] Controlengeurope.com, 'Predictive maintenance cuts costs at paper mill', 2015. [Online]. Available: http://www.controlengeurope.com/article/28795/Predictive-maintenance-cuts-costs-at-paper-mill.aspx. [Accessed: 30- Nov- 2015].

[13] B. G. Lipták, "*Instrument engineers' handbook: process control*", 3rd edition, Chillton, Radnor, 1995.

[14] S. Esposito, 'Evolution of Valve Diagnostics | Flow Control Network', *Flow Control Network*, 2011. [Online]. Available: http://www.flowcontrolnetwork.com/evolution-of-valve-diagnostics/. [Accessed: 30- Nov- 2015].

[15] N. Lindfors and J. Kivelä, "Enhanced maintenance efficiency with third-generation control valve diagnostics," *InTech*, vol. 59, pp. 54-56, Aug 2012 .

[16] Emerson Process Management, "Flow Scanner 6000 Valve Diagnostic System", 2015. [Online]. Available: http://www2.emersonprocess.com/en-us/brands/flowscanner/flowscanner6000valvediagnosticsystem/pages/flowscanner6000valvediagnosticsystem.aspx. [Accessed: 30- Nov- 2015].

[17] A.L.G Carneiro and A.C.S Proto, "Development of an Integrated Condition Monitoring and Diagnostic System for Process Control Valves Used in Nuclear Power Plant," *AIDIC*, vol. 33, pp. 871-876, 2013.

[18] R. Tomovic, *"Introduction to nonlinear automatic control system*", NOLIT, 1966.

[19] K. Ogata, "*Modern control engineering",* Upper Saddle River, N.J: Prentice Hall, 2002.

[20] Z. Liang *et al*, "Physical-Based Modeling of Nonlinearities in Process Control Valves," *in ICCECT, Proceedings of the 2012 International Conference on Control Engineering and Communication Technology*, Liaoning, Dec 2012, pp. 75-78.

[21] M. Choudhury *et al*, "*Diagnosis of Process nonlinearities and valve stiction*", Springer-Verlag, Berlin Heidelberg, 2008.

[22] Blog.opticontrols.com, 'Control Valve Problems', 2015. [Online]. Available: http://blog.opticontrols.com/archives/77. [Accessed: 30- Nov- 2015].

[23] T. Hägglund, "Automatic on-line estimation of backlash in control loops," *Journal of Process Control*, vol. 17, pp. 489-499, 2007.

[24] M. Farenzena and J. O. Trierweiler, "Valve backlash and stiction detection in integrating processes," *in Proceedings of the 8th IFAC Symposium on Advanced Control of Chemical Processes*, Singapore, July 2012, pp. 320 -324.

[25] Documentation.emersonprocess.com, 'Dead Band Plus Hysteresis Estimation with Valve Link Diagnostics', 2015. [Online]. Available: http://www.documentation.emersonprocess.com/groups/public/documents/bulletins/d103549x012.pdf. [Accessed: 30- Nov- 2015].

[26] N. Rinehart, 'The impact of control loop performance on process profitability', 1997. [Online]. Available: http://documentation.emersonprocess.com/groups/public/documents/brochures/d350542x012.pdf. [Accessed: 30- Nov- 2015].

[27] M. Choudhury *et al*, "Modelling valve stiction," *Control Engineering Practice*, vol. 13, pp. 641-658, 2005.

[28] F. D. Jury, "Control Valve Impact on Loop Performance," *Technical monograph*, Emerson Process Management, 2014.

[29] A. W. Ordys *et al*," *Process control performance assessment: from theory to implementation,"* Springer, London, 2007.

[30] M. Choudhury *et al*, "Modelling valve stiction," *Control engineering practice*, vol. 13, pp. 641-658, May, 2005.

[31] M. Jelali, "*Control Performance Management in Industrial Automation,"* Springer Science & Business Media, 2012.

[32] D. N. Govind and S. Bagade Sudheer, "*Process Dynamics and Control,*" PHI Learning Pvt. Ltd., 2011.

[33] M. Hamdan and Z. Gao, "A novel PID controller for pneumatic proportional valves with hysteresis," i*n Proceedings of an Industry Applications Conference, Conference Record of the 2000 IEEE*, Rome, October 2000, vol. 2, pp. 1198-1201, 2

[34] C. Chan and G. Liu, "Hysteresis identification and compensation using a genetic algorithm with adaptive search space," *Mechatronics*, vol. 17, pp. 391-402, 2007.

[35] M. R. Zakerzadeh *et al,* "Hysteresis Nonlinearity Identification Using New Preisach Model-Based Artificial Neural Network Approach," *Journal of Applied Mathematics*, vol. 2011, pp. 1- 22, 15 February 2011.

[36] M. Ruel, "*A simple method to determine control valve performance and its impacts on control loop performance*," Top Control Inc., 2014.

[37] G. C. Goodwin *et al, "A brief overview of nonlinear control," Centre for Integrated Dynamics and Control*, Department of Electrical and Computer Engineering, The University of Newcastle, Australia, 2002.

[38] F. G. Shinskey, "The three faces of control valves," *Control Engineering*, vol. 47, pp. 83- 88, July 2000.

[39] T. Hägglund, "A friction compensator for pneumatic control valves," *Journal of Process Control*, vol. 12, pp. 897-904, 2002.

[40] D. Karthiga and S. Kalaivani, "A new stiction compensation method in pneumatic control valves," *International journal of electronics and computer science engineering*, vol. 1, pp. 2604-2612, September 1, 2012.

[41] R. Srinivasan and R. Rengaswamy, "Approaches for efficient stiction compensation in process control valves," *Computers and Chemical Engineering*, vol. 32, pp. 218-229, 2008.

[42] M. A. de Souza et al, "Improved stiction compensation in pneumatic control valves," *Computers and Chemical Engineering*, vol. 38, pp. 106-114, 2012.

[43] S. Sewdass and P. Govender, "Control Valve Stickband Compensator," *Proceedings of the 19th World Congress, IFAC*, Cape Town, South Africa, 2014.

[44] G. Tao and P. V. Kokotovic, "Adaptive control of plants with unknown hysteresis," *Automatic Control, IEEE Transactions on Automatic Control*, vol. 40, pp. 200-212, Feb 1995.

[45] 'Neural Networks Overview - Matlab and Simulink', 2015. [Online]. Available: http://www.mathworks.com/help/nnet/gs/neural-networks-overview.html. [Accessed: 30- Nov- 2015].

[46] F. M. Dias and A. Antunes, "Fault Torelance of Artifical Neural Networks: an Open Discussion for a Global Model," *International Journal of Circuits, Systems and Signal Processing*, Naun, July, 2008.

[47] D. Heger, 'An introduction to Artifical Neural Networks (ANN) - Methods, Abstraction, and Usage', *Dhtusa.com*, 2015. [Online]. Available: http://www.dhtusa.com/media/NeuralNetworkIntro.pdf. [Accessed: 30- Nov- 2015].

[48] L. Jacobson, 'Introduction to Artificial Neural Networks Part 2 - Learning', 2014. [Online]. Available: http://www.theprojectspot.com/tutorial-post/introduction-to-artificial-neural-networks-part-2-learning/8. [Accessed: 30- Nov- 2015].

[49] 'Time Response Analysis of Feedback Control Systems.', 2015. [Online]. Available: http://elearning.vtu.ac.in/P2/EE43/Ch03/html/0024.htm. [Accessed: 30- Nov- 2015].

[50] S. Sewdass and P. Govender, "Simulation of process control valve stiction," *in Proceedings of the ICCBN, International Conference on Composites, Biocomposites and Nanocomposities*, Durban, December, 2013.

[51] A. Horch and A. Isaksson, "Detection of valve stiction in integrating processes," *in Proceeding of the ECC, European Control Conference*, Porto, Portugal, 2001.

[52] M. Jelali and B. Huang, *Detection and Diagnosis of Stiction in Control Loops State of the Art and Advanced Methods*, Springer- Verlag London, 2010.

[53] M. Ruel, "Valve diagnosis identifies process problems," *in Proceedings of ISA Western Regional Conference and Exhibition*, Las Vegas, NV, 2002.

[54] G. Buckbee, 'How to Identify and Troubleshoot Control Valve Problems 'On the Fly' | Control Engineering', *Controleng.com*, 2001. [Online]. Available: http://www.controleng.com/single-article/how-to-identify-and-troubleshoot-control-valve-problems-on-the-fly/936e955f3c37ac5ac9aee7997f63693d.html. [Accessed: 30- Nov- 2015].

[55] K. E. Moorgas and P. Govender, "Hybrid motion detection system using DSP and ANN ensembles," *Lecture Notes in Engineering and Computer Science*, vol. 2202, no. 1, pp. 484-490, 2013.

[56] C. Stergiou and D. Siganos, 'Neural Networks', *Doc.ic.ac.uk*, 2015. [Online]. Available: http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html. [Accessed: 30- Nov- 2015].

[57] C. Shu and D. Burn, "Artificial neural network ensembles and their application in pooled flood frequency analysis," *Water Resources Research*, vol. 40, issue no. 9 September 2004.

[58] P. Cunningham et al, "Stability Problems with Artificial Neural Networks and the Ensemble Solution," A*rtificial Intelligence in Medicine*, vol. 20, pp. 217-225, November 2000.

[59] Mathworks.com, 'Divide Data for Optimal Neural Network Training - MATLAB & Simulink',2015. [Online]. Available: http://www.mathworks.com/help/nnet/ug/divide-data-for-optimal-neural-network-training.html?searchHighlight=test%20data. [Accessed: 30- Nov- 2015].

[60] X. Yao and M. Islam, "Evolving Artificial Neural Network Ensembles," *IEEE Computational Intelligence Magazine*, vol. 2, no. 1, pp. 31-42, 2008.

[61] D. K. Svozil, V; Pospichal, J, "Introduction to multi-layer feed-forward neural networks," *Chemo metrics and Intelligent Laboratory Systems*, vol. 39, pp. 43-62, 1997.

[62] K. D. Gupta *et al*, "Linear neural network structural design for discrete regions," *International Journal of Engineering Technology and Computer Research*, vol. 1, no 1, pp. 1-5, 2013.

[63] S. Haykin, *Neural Networks: A Comprehensive Foundation*, 2nd ed.: Prentice Hall PTR, 1998.

[64] U. Seiffert and B. Michaelis, "On the gradient descent in backpropagation and its substitution by a gentic algorithm", *Proceedings of the IASTED International Conference on Applied Informatics*, Innsbruck, Austria, 2000.

[65] S. Randall *et al*, "Beyond back propagation: using simulated annealing for training neural networks," *Journal of End User Computing*, vol. 11, pp. 3-10, September 1999.

[66] A. Kowsalya and B. Kannapiran, "Principal component analysis based approach for fault diagnosis in pneumatic valve using Damadics benchmark simulator," *International Journal of research in Engineering and Technology*, vol. 3, 7 May 2014.

APPENDIX

Matlab Code

```
%%%%ANN Ensembles and test data loaded.

load('netP1N10.mat');
load('netP1B20.mat');
load('netP1L31.mat');
load('netP1S10.mat');
load('netP1H20.mat');
load('netP2H20.mat');
load('netP3S10.mat');
load('netP3B20.mat');

load('P1N1.mat');
load('P1B3.mat');
load('P1L1.mat');
load('P1S1.mat');
load('P1H11.mat');
load('P2H1.mat');
load('P3S1.mat');
load('P3B11.mat');

load('P1N22.mat');
load('P1N23.mat');
load('P1N24.mat');

load('P1B22.mat');
load('P1B23.mat');
load('P1B24.mat');

load('P1L21.mat');
load('P1L22.mat');
load('P1L23.mat');

load('P1S22.mat');
load('P1S24.mat');
load('P1S25.mat');

load('P1H16.mat');
load('P1H17.mat');

load('P2H1.mat');
load('P2H2.mat');
load('P2H3.mat');

load('P3S12.mat');
load('P3S13.mat');
load('P3S14.mat');

load('P3B12.mat');
load('P3B13.mat');
load('P3B14.mat');
```

```
%%% Input data are fed into each of the specialised ANNs Ensemble.

InputA = P1N22;

Nt1=sim (netP1N10,InputA);

Nt2=sim (netP1B20,InputA);

Nt3=sim (netP1L31,InputA);

Nt4=sim (netP1S10,InputA);

Nt5=sim (netP1H20,InputA);

Nt6=sim (netP2H20,InputA);

Nt7=sim (netP3S10,InputA);

Nt8=sim (netP3B20,InputA);

%%% The corresponding MSE performance values are calculated.

m1= P1N1- Nt1;
m2= P1B3- Nt2;
m3= P1L1- Nt3;
m4= P1S1- Nt4;
m5= P1H11 - Nt5;
m6= P2H1- Nt6;
m7= P3S1- Nt7;
m8= P3B11- Nt8;

perfA = mse(m1);
perfB = mse(m2);
perfC = mse(m3);
perfD = mse(m4);
perfE = mse(m5);
perfF = mse(m6);
perfG = mse(m7);
perfH = mse(m8);

%%% MSE performance values are compared and used to classify fault
conditions

if perfA < perfB && perfA < perfC && perfA < perfD && perfA < perfE &&
perfA < perfF && perfA < perfG  && perfA < perfH

   disp('No fault')
end


if perfB < perfA && perfB < perfC && perfB < perfD && perfB < perfE &&
perfB < perfF && perfB < perfG && perfB < perfH

   disp('Backlash fault ')
end
```

```
if perfC < perfA && perfC < perfB && perfC < perfD && perfC < perfE &&
perfC < perfF && perfC < perfG && perfC < perfH

   disp('Low air supply ')
end


if perfD < perfA && perfD < perfB && perfD < perfC && perfD < perfE &&
perfD < perfF  && perfD < perfG && perfD < perfH

   disp('Stiction fault ')
end


if perfE < perfA && perfE < perfB && perfE < perfC && perfE < perfD &&
perfE < perfF && perfE < perfG && perfE < perfH

   disp('Hysteresis fault ')
end

if perfF < perfA && perfF < perfB && perfF < perfC && perfF < perfD  &&
perfF < perfE && perfF < perfG && perfF < perfH

   disp('Hysteresis fault plant')
end

if perfG < perfA && perfG < perfB && perfG < perfC && perfG < perfD &&
perfG < perfE && perfG < perfF && perfF < perfH

   disp('Stiction fault ')
end

if perfH < perfA && perfH < perfB && perfH < perfC && perfH < perfD &&
perfH < perfE && perfH < perfF && perfH < perfG

   disp('Backlash fault ')
end
```

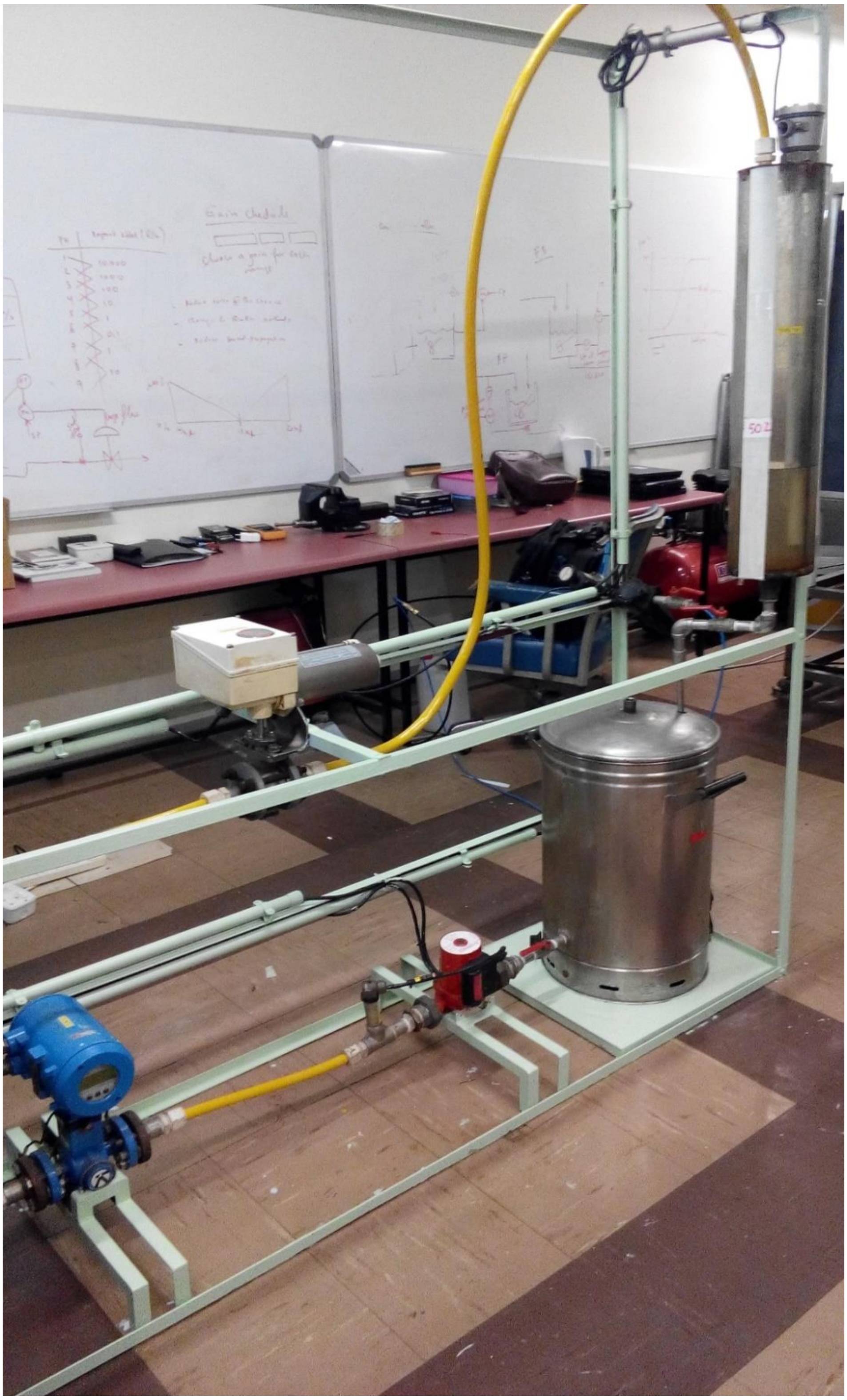
PLANT 1:

Main process plant where the majority of the study was performed.

PLANT 2:

Second process plant used to assess the efficacy of the ensemble fault detector.

PLANT 3:



First process plant used to assess the efficacy of the ensemble fault detector.

P1N22

0.031738	1.176758	3.911133	1.599121	1.228027	3.347168	4.370117	4.379883	4.375	4.375	4.401855	4.39209	4.421387	4.462891	4.54834	4.6875	4.743652	4.799805	4.853516	4.865723	4.899902	4.953613	4.98291	4.98291	4.975586	4.94873	4.943848	5.019531	5.056152	4.892578	4.968262
0.024414	1.374512	3.847656	1.572266	1.252441	3.415527	4.377441	4.370117	4.372559	4.384766	4.389648	4.404297	4.42627	4.465332	4.562988	4.675293	4.73877	4.787598	4.831543	4.87793	4.89502	4.94873	4.953613	4.978027	4.987793	4.94873	4.963379	5.026855	5.041504	4.902344	4.946289
0.031738	1.57959	3.791504	1.518555	1.28418	3.505859	4.394531	4.367676	4.382324	4.362793	4.40918	4.411621	4.438477	4.475098	4.567871	4.6875	4.73877	4.799805	4.855957	4.868164	4.904785	4.958496	4.960938	4.968262	4.975586	4.963379	4.973145	5.031738	5.056152	4.899902	4.956055
0.024414	1.796875	3.742676	1.506348	1.28418	3.566895	4.379883	4.367676	4.367676	4.387207	4.389648	4.404297	4.431152	4.470215	4.580078	4.692383	4.746094	4.804688	4.853516	4.873047	4.902344	4.938965	4.973145	4.968262	4.970703	4.941406	4.958496	5.053711	5.046387	4.890137	4.978027
0.039063	1.99707	3.659668	1.445313	1.337891	3.637695	4.384766	4.367676	4.367676	4.377441	4.384766	4.406738	4.440918	4.460449	4.570313	4.694824	4.743652	4.799805	4.868164	4.875488	4.904785	4.960938	4.953613	4.978027	4.975586	4.941406	4.951172	5.036621	5.053711	4.880371	4.970703
0.029297	2.224121	3.583984	1.416016	1.379395	3.703613	4.401855	4.387207	4.379883	4.39209	4.401855	4.414063	4.448242	4.47998	4.575195	4.70459	4.753418	4.79248	4.841309	4.885254	4.912109	4.946289	4.960938	4.970703	4.968262	4.953613	4.960938	5.03418	5.024414	4.89502	4.98291
0.01709	2.438965	3.505859	1.40625	1.435547	3.757324	4.389648	4.370117	4.367676	4.362793	4.394531	4.389648	4.443359	4.487305	4.589844	4.707031	4.748535	4.812012	4.851074	4.870605	4.899902	4.96582	4.970703	4.973145	4.985352	4.938965	4.968262	5.039063	5.01709	4.882813	4.985352
0.03418	2.663574	3.400879	1.359863	1.452637	3.796387	4.40918	4.360352	4.377441	4.372559	4.394531	4.40918	4.431152	4.489746	4.580078	4.685059	4.768066	4.819336	4.858398	4.868164	4.897461	4.943848	4.973145	4.987793	4.96582	4.94873	4.960938	5.046387	5.029297	4.887695	5.004883
0.026855	2.839355	3.327637	1.347656	1.508789	3.862305	4.418945	4.365234	4.384766	4.379883	4.39209	4.401855	4.438477	4.484863	4.597168	4.707031	4.748535	4.804688	4.855957	4.882813	4.909668	4.951172	4.958496	4.970703	4.985352	4.94873	4.978027	5.056152	5.01709	4.87793	4.997559
0.031738	3.017578	3.239746	1.323242	1.57959	3.916016	4.404297	4.355469	4.372559	4.375	4.396973	4.418945	4.455566	4.489746	4.609375	4.709473	4.743652	4.80957	4.848633	4.873047	4.926758	4.956055	4.973145	4.968262	4.96582	4.951172	4.980469	5.043945	5.009766	4.882813	5.019531
0.026855	3.195801	3.166504	1.298828	1.628418	3.955078	4.401855	4.375	4.367676	4.372559	4.396973	4.394531	4.443359	4.477539	4.606934	4.731445	4.768066	4.819336	4.851074	4.87793	4.924316	4.958496	4.98291	4.96582	4.960938	4.938965	4.953613	5.05127	5	4.875488	5.026855
0.021973	3.317871	3.059082	1.274414	1.70166	3.994141	4.416504	4.362793	4.384766	4.375	4.394531	4.399414	4.450684	4.504395	4.599609	4.697266	4.755859	4.802246	4.863281	4.875488	4.916992	4.946289	4.973145	4.992676	4.970703	4.951172	4.975586	5.039063	5.004883	4.87793	5.026855
0.019531	3.45459	2.963867	1.26709	1.772461	4.038086	4.418945	4.379883	4.384766	4.387207	4.406738	4.411621	4.445801	4.494629	4.621582	4.70459	4.760742	4.819336	4.84375	4.880371	4.919434	4.94873	4.96582	4.980469	4.973145	4.960938	4.978027	5.056152	4.995117	4.885254	5.021973
0.021973	3.569336	2.878418	1.252441	1.843262	4.052734	4.414063	4.355469	4.379883	4.372559	4.396973	4.399414	4.433594	4.519043	4.628906	4.714355	4.755859	4.814453	4.868164	4.875488	4.912109	4.963379	4.973145	4.973145	4.960938	4.946289	4.997559	5.048828	4.995117	4.875488	5.036621
0.041504	3.654785	2.788086	1.23291	1.904297	4.099121	4.418945	4.355469	4.379883	4.382324	4.389648	4.401855	4.443359	4.487305	4.624023	4.699707	4.760742	4.831543	4.873047	4.875488	4.936523	4.94873	4.973145	4.978027	4.958496	4.941406	4.968262	5.068359	4.985352	4.870605	5.056152
0.03418	3.723145	2.709961	1.220703	1.977539	4.123535	4.428711	4.372559	4.384766	4.394531	4.39209	4.411621	4.450684	4.492188	4.633789	4.719238	4.760742	4.804688	4.868164	4.887695	4.924316	4.96582	4.973145	4.973145	4.970703	4.946289	4.973145	5.056152	4.975586	4.880371	5.053711
0.026855	3.813477	2.609863	1.218262	2.072754	4.165039	4.396973	4.362793	4.362793	4.39209	4.404297	4.416504	4.470215	4.51416	4.641113	4.714355	4.763184	4.816895	4.855957	4.887695	4.938965	4.963379	4.980469	4.987793	4.960938	4.943848	4.98291	5.046387	4.960938	4.897461	5.048828
0.036621	3.876953	2.541504	1.181641	2.13623	4.16748	4.411621	4.365234	4.379883	4.377441	4.411621	4.404297	4.448242	4.501953	4.621582	4.726563	4.777832	4.821777	4.865723	4.873047	4.914551	4.963379	4.987793	4.975586	4.968262	4.951172	4.973145	5.065918	4.973145	4.887695	5.065918
0.026855	3.918457	2.441406	1.188965	2.233887	4.189453	4.414063	4.360352	4.375	4.377441	4.396973	4.421387	4.445801	4.511719	4.645996	4.70459	4.770508	4.831543	4.885254	4.880371	4.921875	4.94873	4.958496	4.992676	4.963379	4.951172	4.987793	5.056152	4.980469	4.885254	5.078125
0.036621	3.962402	2.351074	1.169434	2.324219	4.226074	4.42627	4.370117	4.39209	4.394531	4.40918	4.428711	4.450684	4.511719	4.645996	4.719238	4.768066	4.816895	4.865723	4.89502	4.926758	4.968262	4.978027	4.973145	4.960938	4.963379	4.990234	5.061035	4.96582	4.892578	5.080566
0.031738	4.001465	2.290039	1.184082	2.397461	4.230957	4.389648	4.365234	4.360352	4.379883	4.39209	4.418945	4.445801	4.521484	4.667969	4.726563	4.772949	4.819336	4.873047	4.887695	4.936523	4.978027	4.973145	4.968262	4.956055	4.934082	5.004883	5.063477	4.94873	4.890137	5.080566
0.043945	3.999023	2.207031	1.157227	2.485352	4.260254	4.39209	4.365234	4.365234	4.387207	4.404297	4.411621	4.465332	4.516602	4.641113	4.724121	4.770508	4.831543	4.875488	4.885254	4.924316	4.963379	4.997559	4.98291	4.968262	4.956055	4.990234	5.058594	4.946289	4.904785	5.083008
0.024414	4.040527	2.133789	1.154785	2.580566	4.282227	4.404297	4.377441	4.377441	4.39209	4.401855	4.423828	4.453125	4.526367	4.645996	4.719238	4.790039	4.816895	4.855957	4.890137	4.924316	4.963379	4.963379	4.98291	4.970703	4.953613	5	5.056152	4.938965	4.902344	5.078125
0.01709	4.047852	2.058105	1.162109	2.687988	4.291992	4.389648	4.375	4.362793	4.379883	4.416504	4.414063	4.462891	4.538574	4.663086	4.716797	4.777832	4.836426	4.875488	4.885254	4.941406	4.975586	4.96582	4.973145	4.960938	4.968262	5.014648	5.058594	4.94873	4.909668	5.10498
0.036621	4.069824	1.987305	1.154785	2.768555	4.294434	4.399414	4.362793	4.375	4.379883	4.389648	4.431152	4.445801	4.538574	4.648438	4.726563	4.790039	4.84375	4.870605	4.904785	4.929199	4.953613	4.980469	4.96582	4.956055	4.936523	5.012207	5.068359	4.931641	4.899902	5.092773
0.068359	4.042969	1.916504	1.164551	2.84668	4.32373	4.401855	4.375	4.379883	4.387207	4.39209	4.428711	4.450684	4.533691	4.660645	4.724121	4.770508	4.836426	4.885254	4.899902	4.943848	4.970703	4.963379	4.975586	4.963379	4.943848	5.004883	5.063477	4.934082	4.929199	5.10498
0.270996	4.038086	1.865234	1.174316	2.941895	4.326172	4.401855	4.367676	4.377441	4.40918	4.40918	4.440918	4.465332	4.543457	4.667969	4.724121	4.787598	4.829102	4.858398	4.909668	4.941406	4.96582	4.978027	4.975586	4.946289	4.956055	5.007324	5.05127	4.914551	4.916992	5.087891
0.446777	4.042969	1.816406	1.169434	3.010254	4.34082	4.377441	4.384766	4.365234	4.394531	4.396973	4.414063	4.462891	4.536133	4.677734	4.736328	4.780273	4.84375	4.868164	4.892578	4.938965	4.980469	4.978027	4.975586	4.960938	4.941406	5.024414	5.053711	4.929199	4.941406	5.112305
0.610352	4.008789	1.75293	1.169434	3.110352	4.348145	4.379883	4.372559	4.379883	4.387207	4.404297	4.423828	4.462891	4.553223	4.660645	4.731445	4.802246	4.855957	4.868164	4.887695	4.934082	4.94873	4.987793	4.975586	4.94873	4.946289	5.014648	5.056152	4.912109	4.921875	5.102539
0.769043	3.991699	1.696777	1.19873	3.193359	4.375	4.389648	4.384766	4.389648	4.39209	4.406738	4.431152	4.455566	4.54834	4.680176	4.719238	4.780273	4.836426	4.880371	4.904785	4.953613	4.968262	4.956055	4.968262	4.96582	4.951172	5.024414	5.063477	4.929199	4.938965	5.12207
0.974121	3.95752	1.655273	1.21582	3.288574	4.350586	4.375	4.360352	4.377441	4.387207	4.396973	4.438477	4.467773	4.570313	4.694824	4.733887	4.780273	4.848633	4.873047	4.897461	4.958496	4.968262	4.968262	4.963379	4.941406	4.958496	5.021973	5.048828	4.89502	4.946289	5.090332

P1B22

0.026855	0.021973	0.029297	0.014648	0.01709	0.026855	0.014648	0.029297	0.036621	0.029297	0.024414	3.503418	4.362793	4.230957	4.160156	4.145508	4.160156	4.18457	4.204102	4.208984	4.233398	4.206543	4.21875	4.206543	4.248047	4.54834	4.833984	4.921875	4.931641	4.951172	4.938965
0.029297	0.041504	0.036621	0.026855	0.029297	0.01709	0.024414	0.021973	0.01709	0.024414	0.03418	3.586426	4.355469	4.23584	4.162598	4.162598	4.150391	4.160156	4.189453	4.204102	4.199219	4.21875	4.216309	4.21875	4.245605	4.572754	4.841309	4.924316	4.931641	4.958496	4.941406
0.019531	0.014648	0.019531	0.019531	0.031738	0.031738	0.026855	0.024414	0.024414	0.019531	0.024414	3.669434	4.365234	4.233398	4.165039	4.160156	4.165039	4.165039	4.194336	4.213867	4.206543	4.21875	4.216309	4.21875	4.255371	4.592285	4.858398	4.938965	4.951172	4.958496	4.938965
0.026855	0.01709	0.029297	0.021973	0.03418	0.026855	0.039063	0.036621	0.014648	0.019531	0.039063	3.737793	4.34082	4.206543	4.169922	4.174805	4.169922	4.172363	4.196777	4.213867	4.21875	4.23584	4.221191	4.233398	4.248047	4.602051	4.848633	4.909668	4.946289	4.943848	4.956055
0.041504	0.024414	0.031738	0.024414	0.021973	0.026855	0.019531	0.026855	0.036621	0.036621	0.029297	3.803711	4.353027	4.221191	4.152832	4.145508	4.157715	4.16748	4.174805	4.211426	4.196777	4.213867	4.21875	4.213867	4.272461	4.609375	4.868164	4.921875	4.953613	4.938965	4.946289
0.029297	0.012207	0.012207	0.026855	0.036621	0.021973	0.019531	0.021973	0.01709	0.024414	0.046387	3.886719	4.355469	4.21875	4.169922	4.157715	4.150391	4.165039	4.199219	4.20166	4.216309	4.213867	4.213867	4.206543	4.265137	4.616699	4.870605	4.924316	4.953613	4.958496	4.94873
0.019531	0.026855	0.031738	0.019531	0.019531	0.029297	0.031738	0.019531	0.014648	0.01709	0.026855	3.925781	4.350586	4.233398	4.177246	4.160156	4.160156	4.16748	4.189453	4.216309	4.223633	4.21875	4.230957	4.223633	4.291992	4.624023	4.868164	4.934082	4.929199	4.946289	4.936523
0.031738	0.031738	0.01709	0.021973	0.036621	0.021973	0.026855	0.014648	0.026855	0.029297	0.019531	3.974609	4.331055	4.199219	4.157715	4.16748	4.162598	4.174805	4.204102	4.221191	4.221191	4.208984	4.21875	4.213867	4.27002	4.65332	4.863281	4.914551	4.94873	4.951172	4.931641
0.024414	0.026855	0.031738	0.036621	0.024414	0.01709	0.029297	0.026855	0.019531	0.03418	0.036621	4.023438	4.328613	4.20166	4.155273	4.147949	4.165039	4.160156	4.177246	4.213867	4.211426	4.21875	4.211426	4.21875	4.277344	4.650879	4.887695	4.919434	4.946289	4.938965	4.946289
0.031738	0.019531	0.012207	0.03418	0.046387	0.041504	0.031738	0.021973	0.024414	0.031738	0.024414	4.077148	4.338379	4.206543	4.169922	4.150391	4.16748	4.182129	4.187012	4.216309	4.213867	4.206543	4.221191	4.213867	4.301758	4.680176	4.89502	4.929199	4.963379	4.938965	4.941406
0.026855	0.024414	0.01709	0.014648	0.024414	0.026855	0.031738	0.039063	0.026855	0.024414	0.158691	4.116211	4.316406	4.196777	4.16748	4.162598	4.179688	4.189453	4.189453	4.226074	4.230957	4.228516	4.21875	4.208984	4.299316	4.667969	4.885254	4.919434	4.931641	4.953613	4.934082
0.046387	0.036621	0.014648	0.029297	0.01709	0.021973	0.024414	0.009766	0.024414	0.03418	0.317383	4.140625	4.326172	4.194336	4.162598	4.147949	4.150391	4.177246	4.18457	4.196777	4.211426	4.213867	4.230957	4.206543	4.316406	4.682617	4.892578	4.931641	4.936523	4.94873	4.931641
0.009766	0.021973	0.014648	0.029297	0.031738	0.024414	0.024414	0.024414	0.019531	0.021973	0.461426	4.18457	4.306641	4.191895	4.169922	4.162598	4.16748	4.169922	4.18457	4.216309	4.216309	4.211426	4.221191	4.216309	4.32373	4.699707	4.902344	4.936523	4.94873	4.968262	4.936523
0.024414	0.019531	0.014648	0.024414	0.026855	0.031738	0.039063	0.019531	0.019531	0.039063	0.603027	4.196777	4.291992	4.199219	4.174805	4.165039	4.165039	4.187012	4.191895	4.211426	4.21875	4.223633	4.233398	4.228516	4.328613	4.70459	4.880371	4.929199	4.934082	4.951172	4.936523
0.026855	0.031738	0.019531	0.024414	0.026855	0.031738	0.024414	0.036621	0.031738	0.026855	0.771484	4.233398	4.304199	4.187012	4.145508	4.157715	4.179688	4.179688	4.196777	4.230957	4.20166	4.21875	4.211426	4.221191	4.331055	4.711914	4.904785	4.916992	4.951172	4.946289	4.931641
0.039063	0.01709	0.021973	0.036621	0.024414	0.021973	0.021973	0.009766	0.03418	0.046387	0.952148	4.250488	4.296875	4.199219	4.16748	4.150391	4.155273	4.179688	4.18457	4.204102	4.221191	4.211426	4.213867	4.213867	4.353027	4.724121	4.89502	4.936523	4.951172	4.94873	4.941406
0.01709	0.029297	0.019531	0.014648	0.031738	0.03418	0.021973	0.014648	0.019531	0.021973	1.125488	4.284668	4.309082	4.204102	4.162598	4.162598	4.157715	4.187012	4.20166	4.204102	4.216309	4.211426	4.226074	4.21875	4.377441	4.73877	4.914551	4.936523	4.953613	4.941406	4.943848
0.01709	0.021973	0.024414	0.036621	0.019531	0.01709	0.019531	0.024414	0.026855	0.01709	1.303711	4.287109	4.272461	4.191895	4.174805	4.174805	4.169922	4.196777	4.211426	4.221191	4.230957	4.21875	4.223633	4.208984	4.377441	4.731445	4.887695	4.929199	4.936523	4.956055	4.934082
0.029297	0.039063	0.03418	0.026855	0.021973	0.03418	0.03418	0.01709	0.019531	0.031738	1.513672	4.301758	4.277344	4.179688	4.145508	4.157715	4.157715	4.16748	4.199219	4.206543	4.204102	4.21875	4.21875	4.223633	4.387207	4.755859	4.89502	4.938965	4.941406	4.953613	4.936523
0.024414	0.009766	0.019531	0.043945	0.03418	0.03418	0.026855	0.024414	0.029297	0.026855	1.728516	4.326172	4.277344	4.179688	4.150391	4.162598	4.16748	4.187012	4.189453	4.21875	4.208984	4.213867	4.213867	4.213867	4.404297	4.775391	4.904785	4.943848	4.963379	4.960938	4.934082
0.031738	0.021973	0.014648	0.01709	0.029297	0.039063	0.043945	0.029297	0.021973	0.024414	1.921387	4.326172	4.267578	4.199219	4.160156	4.16748	4.172363	4.179688	4.204102	4.21875	4.216309	4.228516	4.21875	4.233398	4.399414	4.765625	4.89502	4.916992	4.946289	4.931641	4.951172
0.03418	0.019531	0.029297	0.01709	0.01709	0.029297	0.009766	0.024414	0.036621	0.021973	2.114258	4.338379	4.262695	4.187012	4.145508	4.143066	4.16748	4.20166	4.196777	4.213867	4.20166	4.208984	4.21875	4.213867	4.438477	4.768066	4.899902	4.941406	4.956055	4.941406	4.941406
0.026855	0.031738	0.029297	0.03418	0.024414	0.019531	0.029297	0.019531	0.012207	0.026855	2.30957	4.350586	4.257813	4.191895	4.160156	4.165039	4.160156	4.174805	4.206543	4.206543	4.221191	4.211426	4.21875	4.208984	4.433594	4.780273	4.902344	4.936523	4.951172	4.94873	4.951172
0.021973	0.012207	0.029297	0.026855	0.03418	0.036621	0.026855	0.024414	0.03418	0.031738	2.48291	4.348145	4.262695	4.194336	4.162598	4.155273	4.174805	4.174805	4.206543	4.216309	4.208984	4.211426	4.223633	4.228516	4.467773	4.794922	4.912109	4.953613	4.931641	4.943848	4.929199
0.029297	0.014648	0.021973	0.029297	0.036621	0.026855	0.041504	0.03418	0.01709	0.029297	2.658691	4.362793	4.248047	4.165039	4.160156	4.172363	4.182129	4.189453	4.221191	4.230957	4.226074	4.21875	4.216309	4.221191	4.453125	4.804688	4.89502	4.926758	4.951172	4.943848	4.926758
0.036621	0.026855	0.03418	0.026855	0.024414	0.029297	0.014648	0.024414	0.041504	0.031738	2.805176	4.35791	4.250488	4.187012	4.150391	4.145508	4.172363	4.174805	4.187012	4.213867	4.206543	4.226074	4.204102	4.226074	4.470215	4.80957	4.914551	4.929199	4.94873	4.946289	4.943848
0.021973	0.024414	0.012207	0.024414	0.031738	0.021973	0.01709	0.01709	0.019531	0.026855	2.958984	4.382324	4.257813	4.179688	4.162598	4.150391	4.169922	4.187012	4.20166	4.221191	4.211426	4.213867	4.21875	4.226074	4.494629	4.829102	4.926758	4.943848	4.968262	4.946289	4.934082
0.029297	0.029297	0.029297	0.026855	0.026855	0.019531	0.029297	0.029297	0.014648	0.01709	3.066406	4.360352	4.245605	4.194336	4.172363	4.155273	4.177246	4.187012	4.206543	4.223633	4.230957	4.221191	4.221191	4.221191	4.494629	4.80957	4.912109	4.926758	4.938965	4.946289	4.936523
0.036621	0.024414	0.019531	0.024414	0.03418	0.03418	0.019531	0.01709	0.029297	0.031738	3.186035	4.362793	4.230957	4.160156	4.157715	4.147949	4.155273	4.189453	4.213867	4.199219	4.213867	4.213867	4.228516	4.216309	4.519043	4.829102	4.909668	4.943848	4.936523	4.936523	4.936523
0.009766	0.019531	0.039063	0.036621	0.01709	0.026855	0.024414	0.024414	0.021973	0.036621	3.312988	4.360352	4.233398	4.165039	4.155273	4.150391	4.177246	4.179688	4.196777	4.221191	4.21875	4.211426	4.216309	4.226074	4.528809	4.831543	4.914551	4.94873	4.94873	4.956055	4.936523
0.029297	0.01709	0.014648	0.03418	0.041504	0.043945	0.029297	0.019531	0.024414	0.029297	3.410645	4.367676	4.245605	4.177246	4.165039	4.152832	4.165039	4.191895	4.199219	4.21875	4.216309	4.223633	4.226074	4.250488	4.543457	4.853516	4.914551	4.943848	4.943848	4.951172	4.934082

P1L22

0.026855	0.021973	0.041504	0.031738	3.735352	3.376465	2.785645	2.695313	3.000488	3.933105	4.226074	3.935547	4.047852	4.697266	4.882813	4.587402	4.538574	4.736328	4.921875	4.997559	4.902344	4.868164	4.892578	4.96582	5.012207	5.004883	5.014648	4.978027	4.975586	4.968262	4.963379
0.024414	0.046387	0.031738	0.03418	3.80127	3.366699	2.775879	2.700195	3.024902	3.972168	4.233398	3.918457	4.050293	4.709473	4.887695	4.567871	4.521484	4.731445	4.938965	4.997559	4.907227	4.855957	4.897461	4.960938	5	5.002441	5.009766	4.975586	4.960938	4.963379	4.960938
0.036621	0.03418	0.03418	0.021973	3.869629	3.322754	2.773438	2.680664	3.044434	3.991699	4.21875	3.920898	4.084473	4.736328	4.868164	4.553223	4.543457	4.753418	4.936523	4.98291	4.897461	4.870605	4.890137	4.968262	5.002441	5.01709	5.014648	4.968262	4.980469	4.973145	4.96582
0.029297	0.031738	0.026855	0.039063	3.911133	3.291016	2.758789	2.705078	3.066406	4.02832	4.196777	3.90625	4.094238	4.750977	4.865723	4.558105	4.541016	4.755859	4.943848	4.995117	4.912109	4.865723	4.892578	4.956055	5.012207	5.009766	5.002441	4.968262	4.968262	4.970703	4.951172
0.029297	0.03418	0.039063	0.036621	3.952637	3.254395	2.749023	2.69043	3.098145	4.038086	4.194336	3.916016	4.11377	4.768066	4.84375	4.543457	4.543457	4.753418	4.931641	4.987793	4.902344	4.855957	4.890137	4.978027	5	5.014648	4.997559	4.987793	4.970703	4.973145	4.953613
0.024414	0.026855	0.039063	0.021973	3.977051	3.222656	2.758789	2.692871	3.125	4.069824	4.191895	3.908691	4.130859	4.780273	4.848633	4.550781	4.54834	4.765625	4.951172	4.987793	4.897461	4.865723	4.904785	4.973145	5	5	5.009766	4.975586	4.970703	4.958496	4.960938
0.03418	0.041504	0.036621	0.029297	4.008789	3.210449	2.736816	2.702637	3.14209	4.094238	4.174805	3.891602	4.143066	4.80957	4.829102	4.536133	4.550781	4.777832	4.951172	4.98291	4.882813	4.86084	4.902344	4.963379	4.995117	5.009766	5.002441	4.978027	4.960938	4.978027	4.951172
0.031738	0.03418	0.024414	0.029297	4.023438	3.17627	2.734375	2.697754	3.193359	4.108887	4.169922	3.903809	4.174805	4.814453	4.807129	4.528809	4.562988	4.785156	4.941406	4.975586	4.904785	4.865723	4.904785	4.973145	5.007324	5.014648	5	4.96582	4.970703	4.970703	4.946289
0.03418	0.029297	0.046387	0.12207	4.035645	3.149414	2.729492	2.714844	3.208008	4.130859	4.143066	3.88916	4.191895	4.833984	4.804688	4.533691	4.570313	4.799805	4.953613	4.98291	4.890137	4.863281	4.892578	4.968262	5.007324	5	4.995117	4.968262	4.973145	4.956055	4.94873
0.01709	0.036621	0.03418	0.253906	4.020996	3.122559	2.724609	2.712402	3.22998	4.143066	4.150391	3.896484	4.213867	4.831543	4.787598	4.519043	4.575195	4.790039	4.951172	4.985352	4.885254	4.853516	4.919434	4.980469	5.009766	5.007324	5.002441	4.980469	4.973145	4.963379	4.953613
0.041504	0.03418	0.03418	0.356445	4.035645	3.098145	2.729492	2.722168	3.271484	4.172363	4.130859	3.894043	4.228516	4.863281	4.782715	4.519043	4.577637	4.814453	4.973145	4.978027	4.87793	4.86084	4.904785	4.980469	4.995117	5	5.004883	4.970703	4.96582	4.958496	4.958496
0.031738	0.03418	0.026855	0.466309	4.016113	3.081055	2.70752	2.719727	3.295898	4.18457	4.106445	3.884277	4.260254	4.865723	4.770508	4.519043	4.594727	4.807129	4.96582	4.970703	4.875488	4.873047	4.912109	4.973145	5.019531	5.01709	5.007324	4.973145	4.978027	4.968262	4.956055
0.019531	0.03418	0.024414	0.627441	3.999023	3.061523	2.709961	2.741699	3.337402	4.196777	4.101563	3.88916	4.284668	4.865723	4.760742	4.511719	4.597168	4.80957	4.963379	4.980469	4.882813	4.86084	4.904785	4.980469	5.004883	5.012207	4.98291	4.968262	4.973145	4.963379	4.943848
0.024414	0.029297	0.036621	0.766602	3.984375	3.024902	2.709961	2.739258	3.356934	4.204102	4.084473	3.898926	4.311523	4.882813	4.746094	4.523926	4.609375	4.821777	4.963379	4.973145	4.875488	4.868164	4.907227	4.992676	5.004883	5.007324	5.009766	4.968262	4.978027	4.953613	4.968262
0.021973	0.043945	0.029297	0.935059	3.95752	3.024902	2.700195	2.751465	3.38623	4.238281	4.091797	3.891602	4.316406	4.882813	4.741211	4.509277	4.602051	4.82666	4.985352	4.980469	4.873047	4.858398	4.921875	4.978027	5	5.002441	4.995117	4.973145	4.963379	4.960938	4.953613
0.029297	0.039063	0.029297	1.11084	3.94043	2.998047	2.697754	2.746582	3.427734	4.233398	4.069824	3.891602	4.360352	4.907227	4.726563	4.506836	4.621582	4.84375	4.975586	4.963379	4.868164	4.873047	4.916992	4.985352	4.997559	5.021973	4.987793	4.973145	4.973145	4.968262	4.951172
0.031738	0.026855	0.021973	1.291504	3.913574	2.96875	2.692871	2.766113	3.457031	4.248047	4.060059	3.891602	4.370117	4.909668	4.719238	4.511719	4.626465	4.841309	4.985352	4.970703	4.875488	4.875488	4.914551	4.98291	5.009766	5.004883	4.990234	4.96582	4.970703	4.958496	4.951172
0.024414	0.039063	0.03418	1.503906	3.886719	2.956543	2.695313	2.780762	3.48877	4.245605	4.042969	3.908691	4.39209	4.912109	4.694824	4.504395	4.626465	4.853516	4.973145	4.96582	4.870605	4.863281	4.916992	4.992676	5.002441	5.012207	4.980469	4.985352	4.958496	4.96582	4.946289
0.021973	0.036621	0.031738	1.70166	3.845215	2.939453	2.697754	2.775879	3.525391	4.25293	4.047852	3.911133	4.418945	4.914551	4.70459	4.511719	4.63623	4.851074	4.987793	4.958496	4.875488	4.875488	4.929199	4.995117	5.01709	5.007324	4.992676	4.973145	4.968262	4.956055	4.958496
0.041504	0.03418	0.031738	1.899414	3.825684	2.93457	2.695313	2.790527	3.557129	4.27002	4.025879	3.903809	4.431152	4.926758	4.680176	4.49707	4.638672	4.870605	4.987793	4.956055	4.858398	4.873047	4.931641	4.98291	4.997559	5.012207	4.98291	4.963379	4.958496	4.963379	4.951172
0.03418	0.031738	0.01709	2.109375	3.78418	2.915039	2.680664	2.805176	3.598633	4.267578	4.020996	3.925781	4.467773	4.926758	4.660645	4.504395	4.65332	4.868164	4.975586	4.946289	4.87793	4.868164	4.934082	4.995117	5.004883	5.014648	4.987793	4.975586	4.973145	4.963379	4.953613
0.03418	0.026855	0.039063	2.316895	3.757324	2.897949	2.702637	2.819824	3.630371	4.272461	3.999023	3.92334	4.489746	4.934082	4.658203	4.504395	4.658203	4.882813	4.987793	4.951172	4.868164	4.873047	4.921875	4.987793	5.004883	5.002441	4.978027	4.968262	4.96582	4.943848	4.94873
0.019531	0.036621	0.031738	2.526855	3.708496	2.880859	2.692871	2.839355	3.649902	4.27002	4.001465	3.935547	4.511719	4.919434	4.641113	4.501953	4.67041	4.870605	4.985352	4.94873	4.855957	4.868164	4.94873	4.987793	5.009766	5.007324	4.987793	4.973145	4.96582	4.958496	4.960938
0.029297	0.039063	0.019531	2.731934	3.679199	2.875977	2.695313	2.84668	3.701172	4.282227	3.989258	3.94043	4.528809	4.936523	4.643555	4.504395	4.67041	4.897461	4.992676	4.941406	4.863281	4.87793	4.938965	4.990234	4.995117	5.007324	4.980469	4.96582	4.956055	4.951172	4.956055
0.039063	0.036621	0.021973	2.905273	3.642578	2.858887	2.685547	2.856445	3.725586	4.277344	3.967285	3.942871	4.56543	4.924316	4.628906	4.499512	4.689941	4.890137	4.992676	4.934082	4.855957	4.880371	4.931641	4.990234	5.014648	5.002441	4.98291	4.960938	4.978027	4.94873	4.963379
0.024414	0.026855	0.019531	3.088379	3.596191	2.851563	2.683105	2.897949	3.754883	4.277344	3.967285	3.964844	4.577637	4.914551	4.621582	4.506836	4.6875	4.887695	4.985352	4.946289	4.870605	4.87793	4.938965	4.995117	5.007324	5.002441	4.968262	4.968262	4.96582	4.951172	4.94873
0.029297	0.041504	0.03418	3.220215	3.562012	2.82959	2.692871	2.900391	3.786621	4.257813	3.95752	3.969727	4.611816	4.916992	4.609375	4.519043	4.709473	4.897461	4.992676	4.931641	4.863281	4.875488	4.929199	5	4.995117	5	4.985352	4.968262	4.963379	4.946289	4.968262
0.029297	0.039063	0.026855	3.347168	3.518066	2.82959	2.687988	2.919922	3.811035	4.277344	3.95752	3.984375	4.614258	4.904785	4.606934	4.51416	4.689941	4.897461	5.004883	4.936523	4.86084	4.892578	4.953613	4.997559	5.002441	5.004883	4.975586	4.963379	4.958496	4.953613	4.960938
0.039063	0.043945	0.026855	3.479004	3.498535	2.819824	2.685547	2.932129	3.850098	4.260254	3.947754	3.989258	4.650879	4.916992	4.594727	4.511719	4.72168	4.919434	4.990234	4.916992	4.855957	4.880371	4.94873	4.992676	5	5.012207	4.968262	4.963379	4.958496	4.953613	4.951172
0.039063	0.031738	0.026855	3.566895	3.459473	2.79541	2.683105	2.95166	3.881836	4.245605	3.935547	4.013672	4.658203	4.902344	4.589844	4.526367	4.719238	4.914551	4.995117	4.919434	4.873047	4.897461	4.953613	5.007324	5.009766	5.009766	4.973145	4.968262	4.973145	4.953613	4.958496
0.029297	0.041504	0.03418	3.669434	3.422852	2.79541	2.692871	2.98584	3.908691	4.240723	3.930664	4.02832	4.672852	4.897461	4.575195	4.53125	4.719238	4.919434	4.987793	4.921875	4.863281	4.882813	4.951172	4.995117	5.004883	4.997559	4.970703	4.970703	4.96582	4.94873	4.958496

APPENDIX 3: EXAMPLES OF DATASETS

P1S22

0.029297	0.039063	0.024414	0.01709	1.418457	6.276855	7.075195	6.955566	6.655273	4.833984	1.057129	0.341797	5.13916	6.853027	7.109375	6.977539	6.833496	6.550293	2.768555	0.473633	2.163086	6.115723	7.038574	7.058105	6.92627	6.757813	5.429688	1.306152	0.146484	4.541016	6.750488
0.036621	0.029297	0.029297	0.036621	1.616211	6.352539	7.089844	6.933594	6.645508	4.65332	1.003418	0.449219	5.236816	6.89209	7.102051	6.97998	6.831055	6.52832	2.636719	0.427246	2.363281	6.152344	7.041016	7.050781	6.916504	6.728516	5.253906	1.218262	0.131836	4.655762	6.774902
0.021973	0.03418	0.036621	0.029297	1.853027	6.428223	7.075195	6.931152	6.640625	4.484863	0.95459	0.561523	5.344238	6.899414	7.109375	6.989746	6.809082	6.518555	2.495117	0.400391	2.548828	6.213379	7.058105	7.038574	6.923828	6.740723	5.092773	1.152344	0.153809	4.79248	6.804199
0.019531	0.031738	0.024414	0.031738	2.080078	6.469727	7.087402	6.940918	6.621094	4.311523	0.881348	0.715332	5.422363	6.914063	7.116699	6.984863	6.816406	6.516113	2.380371	0.380859	2.736816	6.276855	7.050781	7.04834	6.899414	6.726074	4.924316	1.096191	0.19043	4.916992	6.816406
0.031738	0.029297	0.026855	0.031738	2.297363	6.52832	7.084961	6.914063	6.628418	4.152832	0.837402	0.878906	5.537109	6.936035	7.084961	6.970215	6.821289	6.491699	2.270508	0.32959	2.907715	6.315918	7.053223	7.036133	6.914063	6.708984	4.746094	1.020508	0.236816	5.053711	6.848145
0.026855	0.021973	0.03418	0.026855	2.502441	6.574707	7.077637	6.914063	6.628418	3.986816	0.793457	1.032715	5.620117	6.943359	7.092285	6.967773	6.787109	6.459961	2.165527	0.317383	3.095703	6.384277	7.067871	7.036133	6.918945	6.691895	4.580078	0.979004	0.32959	5.13916	6.865234
0.024414	0.029297	0.014648	0.01709	2.734375	6.616211	7.06543	6.906738	6.59668	3.828125	0.725098	1.186523	5.722656	6.977539	7.089844	6.955566	6.784668	6.42334	2.053223	0.292969	3.237305	6.437988	7.060547	7.028809	6.906738	6.694336	4.411621	0.913086	0.412598	5.234375	6.899414
0.021973	0.039063	0.029297	0.029297	2.937012	6.665039	7.077637	6.884766	6.594238	3.671875	0.693359	1.367188	5.773926	6.97998	7.08252	6.967773	6.782227	6.340332	1.938477	0.273438	3.413086	6.481934	7.077637	7.019043	6.90918	6.682129	4.233398	0.871582	0.554199	5.344238	6.899414
0.039063	0.039063	0.024414	0.036621	3.161621	6.704102	7.062988	6.877441	6.594238	3.518066	0.649414	1.530762	5.847168	7.009277	7.08252	6.950684	6.760254	6.259766	1.848145	0.241699	3.588867	6.508789	7.092285	7.009277	6.916504	6.679688	4.072266	0.79834	0.678711	5.437012	6.911621
0.019531	0.024414	0.041504	0.029297	3.356934	6.767578	7.070313	6.867676	6.560059	3.356934	0.620117	1.726074	5.935059	6.994629	7.06543	6.965332	6.765137	6.159668	1.743164	0.229492	3.730469	6.552734	7.084961	7.006836	6.884766	6.665039	3.903809	0.754395	0.842285	5.527344	6.940918
0.019531	0.041504	0.021973	0.024414	3.574219	6.787109	7.060547	6.872559	6.557617	3.212891	0.563965	1.904297	5.993652	7.004395	7.080078	6.943359	6.757813	6.035156	1.650391	0.212402	3.901367	6.59668	7.089844	7.019043	6.887207	6.672363	3.759766	0.717773	0.991211	5.620117	6.940918
0.026855	0.01709	0.019531	0.036621	3.754883	6.809082	7.070313	6.862793	6.54541	3.066406	0.529785	2.099609	6.064453	7.03125	7.058105	6.933594	6.760254	5.905762	1.569824	0.192871	4.050293	6.633301	7.102051	7.011719	6.884766	6.643066	3.591309	0.67627	1.157227	5.710449	6.967773
0.014648	0.026855	0.029297	0.019531	3.937988	6.84082	7.043457	6.838379	6.540527	2.932129	0.500488	2.270508	6.142578	7.023926	7.053223	6.943359	6.728516	5.776367	1.481934	0.180664	4.189453	6.660156	7.077637	7.001953	6.877441	6.630859	3.449707	0.634766	1.337891	5.788574	6.994629
0.026855	0.024414	0.019531	0.026855	4.135742	6.867676	7.038574	6.84082	6.508789	2.788086	0.466309	2.451172	6.193848	7.04834	7.062988	6.923828	6.723633	5.620117	1.403809	0.180664	4.321289	6.71875	7.094727	7.006836	6.887207	6.635742	3.278809	0.600586	1.503906	5.856934	6.994629
0.03418	0.024414	0.031738	0.029297	4.289551	6.894531	7.04834	6.818848	6.494141	2.670898	0.43457	2.641602	6.237793	7.062988	7.045898	6.936035	6.728516	5.456543	1.325684	0.146484	4.470215	6.730957	7.092285	6.984863	6.867676	6.606445	3.120117	0.556641	1.706543	5.935059	7.001953
0.036621	0.024414	0.039063	0.03418	4.47998	6.921387	7.023926	6.806641	6.486816	2.531738	0.41748	2.807617	6.296387	7.053223	7.043457	6.936035	6.711426	5.302734	1.252441	0.144043	4.592285	6.755371	7.106934	6.97998	6.879883	6.61377	2.998047	0.515137	1.901855	5.996094	7.021484
0.026855	0.029297	0.029297	0.024414	4.63623	6.948242	7.038574	6.811523	6.45752	2.399902	0.378418	2.995605	6.345215	7.058105	7.036133	6.923828	6.706543	5.148926	1.176758	0.144043	4.729004	6.782227	7.089844	6.97998	6.855469	6.606445	2.858887	0.478516	2.077637	6.074219	7.009277
0.021973	0.024414	0.024414	0.021973	4.790039	6.960449	7.033691	6.787109	6.447754	2.290039	0.356445	3.183594	6.398926	7.084961	7.026367	6.90918	6.70166	4.963379	1.120605	0.146484	4.841309	6.811523	7.084961	6.962891	6.845703	6.584473	2.719727	0.446777	2.260742	6.152344	7.041016
0.043945	0.026855	0.026855	0.024414	4.926758	6.967773	7.023926	6.787109	6.44043	2.177734	0.322266	3.339844	6.437988	7.072754	7.023926	6.921387	6.68457	4.802246	1.064453	0.212402	4.970703	6.845703	7.097168	6.970215	6.85791	6.557617	2.595215	0.422363	2.458496	6.206055	7.041016
0.029297	0.031738	0.024414	0.024414	5.073242	6.989746	7.004395	6.77002	6.384277	2.060547	0.29541	3.508301	6.506348	7.092285	7.023926	6.896973	6.66748	4.638672	0.998535	0.283203	5.063477	6.865234	7.080078	6.965332	6.845703	6.557617	2.463379	0.383301	2.619629	6.254883	7.067871
0.036621	0.041504	0.031738	0.021973	5.222168	7.001953	7.019043	6.757813	6.333008	1.970215	0.27832	3.679199	6.533203	7.089844	7.033691	6.90918	6.660156	4.443359	0.932617	0.393066	5.166016	6.896973	7.089844	6.962891	6.84082	6.538086	2.338867	0.378418	2.817383	6.311035	7.04834
0.036621	0.029297	0.029297	0.039063	5.341797	7.016602	7.004395	6.740723	6.26709	1.862793	0.266113	3.813477	6.564941	7.109375	7.016602	6.896973	6.665039	4.287109	0.88623	0.495605	5.285645	6.904297	7.104492	6.945801	6.835938	6.516113	2.231445	0.339355	2.993164	6.352539	7.045898
0.024414	0.029297	0.043945	0.029297	5.471191	7.043457	7.004395	6.748047	6.147461	1.762695	0.258789	3.974609	6.601563	7.089844	7.01416	6.906738	6.665039	4.121094	0.820313	0.627441	5.366211	6.914063	7.08252	6.958008	6.818848	6.477051	2.109375	0.307617	3.181152	6.416016	7.06543
0.021973	0.036621	0.024414	0.026855	5.600586	7.045898	7.001953	6.748047	6.052246	1.677246	0.224609	4.125977	6.633301	7.092285	7.011719	6.877441	6.647949	3.95752	0.773926	0.783691	5.480957	6.938477	7.084961	6.955566	6.806641	6.445313	2.019043	0.29541	3.330078	6.459961	7.053223
0.026855	0.014648	0.019531	0.114746	5.681152	7.04834	7.009277	6.733398	5.927734	1.569824	0.195313	4.282227	6.674805	7.111816	6.99707	6.870117	6.645508	3.78418	0.725098	0.927734	5.571289	6.953125	7.080078	6.943359	6.804199	6.347656	1.901855	0.270996	3.491211	6.508789	7.06543
0.026855	0.026855	0.029297	0.290527	5.786133	7.055664	6.970215	6.713867	5.808105	1.499023	0.187988	4.399414	6.706543	7.092285	6.999512	6.879883	6.630859	3.632813	0.681152	1.086426	5.651855	6.967773	7.06543	6.945801	6.801758	6.252441	1.813965	0.256348	3.664551	6.540527	7.077637
0.041504	0.019531	0.01709	0.480957	5.888672	7.060547	6.975098	6.708984	5.639648	1.408691	0.168457	4.528809	6.743164	7.114258	7.009277	6.850586	6.606445	3.479004	0.634766	1.274414	5.722656	6.99707	7.070313	6.958008	6.806641	6.152344	1.704102	0.231934	3.811035	6.577148	7.080078
0.029297	0.029297	0.03418	0.629883	5.974121	7.087402	6.975098	6.687012	5.480957	1.347656	0.158691	4.667969	6.762695	7.109375	7.001953	6.865234	6.61377	3.322754	0.600586	1.44043	5.817871	7.006836	7.058105	6.923828	6.787109	6.013184	1.611328	0.224609	3.977051	6.623535	7.072754
0.039063	0.01709	0.029297	0.830078	6.062012	7.077637	6.958008	6.68457	5.332031	1.252441	0.17334	4.777832	6.782227	7.111816	6.99707	6.85791	6.586914	3.17627	0.561523	1.628418	5.88623	7.009277	7.08252	6.928711	6.791992	5.895996	1.535645	0.195313	4.133301	6.645508	7.075195
0.031738	0.019531	0.039063	1.000977	6.137695	7.099609	6.960449	6.674805	5.161133	1.186523	0.209961	4.912109	6.813965	7.099609	6.982422	6.848145	6.586914	3.051758	0.522461	1.809082	5.966797	7.021484	7.06543	6.92627	6.762695	5.74707	1.452637	0.166016	4.267578	6.68457	7.070313
0.01709	0.024414	0.029297	1.201172	6.223145	7.077637	6.945801	6.665039	4.997559	1.120605	0.26123	5.039063	6.831055	7.102051	6.984863	6.828613	6.564941	2.897949	0.493164	1.987305	6.035156	7.021484	7.055664	6.916504	6.750488	5.600586	1.376953	0.161133	4.404297	6.728516	7.075195

P1H16

0.039063	0.932617	3.149414	1.806641	2.861328	5.095215	5.537109	5.581055	5.493164	5.332031	5.307617	5.234375	5.17334	5.097656	5.126953	5.102539	5.063477	5.039063	5.05127	5.063477	5.01709	4.987793	5.03418	5.031738	4.987793	4.990234	5.021973	5.024414	4.990234	4.968262	5.024414
0.024414	1.123047	3.110352	1.772461	2.971191	5.119629	5.539551	5.583496	5.466309	5.341797	5.300293	5.251465	5.168457	5.112305	5.112305	5.100098	5.043945	5.036621	5.068359	5.053711	5.014648	4.997559	5.019531	5.041504	4.990234	4.997559	5.041504	5	4.990234	4.960938	5.024414
0.01709	1.337891	3.039551	1.765137	3.07373	5.146484	5.546875	5.593262	5.454102	5.334473	5.302734	5.234375	5.161133	5.109863	5.107422	5.083008	5.053711	5.039063	5.05127	5.075684	5	5.004883	5.021973	5.036621	4.987793	4.985352	5.036621	5.021973	4.98291	4.987793	5.026855
0.041504	1.54541	2.990723	1.738281	3.17627	5.178223	5.549316	5.57373	5.473633	5.32959	5.285645	5.236816	5.17334	5.102539	5.12207	5.075684	5.05127	5.031738	5.056152	5.056152	5.009766	4.997559	5.043945	5.029297	4.970703	5.007324	5.029297	5.014648	4.987793	4.980469	5.046387
0.031738	1.762695	2.93457	1.721191	3.278809	5.20752	5.529785	5.588379	5.463867	5.32959	5.280762	5.249023	5.153809	5.112305	5.100098	5.097656	5.048828	5.014648	5.068359	5.063477	5.002441	5.007324	5.036621	5.05127	4.970703	4.995117	5.039063	5	4.98291	4.987793	5.029297
0.024414	1.994629	2.861328	1.704102	3.369141	5.219727	5.544434	5.581055	5.456543	5.317383	5.300293	5.222168	5.170898	5.102539	5.107422	5.090332	5.053711	5.036621	5.043945	5.065918	4.992676	4.992676	5.048828	5.03418	4.98291	4.997559	5.03418	5.014648	4.963379	4.980469	5.036621
0.036621	2.199707	2.817383	1.694336	3.459473	5.249023	5.556641	5.578613	5.437012	5.332031	5.275879	5.239258	5.170898	5.087891	5.109863	5.092773	5.039063	5.026855	5.065918	5.053711	5.014648	4.985352	5.039063	5.03418	4.963379	5.002441	5.039063	5.012207	4.992676	4.978027	5.031738
0.029297	2.434082	2.756348	1.677246	3.57666	5.268555	5.559082	5.583496	5.427246	5.314941	5.290527	5.229492	5.158691	5.109863	5.107422	5.075684	5.048828	5.019531	5.058594	5.058594	4.990234	5.01709	5.041504	5.031738	4.970703	4.995117	5.039063	4.997559	4.985352	5.002441	5.024414
0.03418	2.65625	2.69043	1.669922	3.659668	5.290527	5.559082	5.568848	5.437012	5.314941	5.290527	5.219727	5.158691	5.10498	5.131836	5.075684	5.039063	5.026855	5.05127	5.053711	4.995117	5.004883	5.056152	5.026855	4.978027	5	5.01709	5.007324	4.985352	4.987793	5.039063
0.031738	2.854004	2.648926	1.645508	3.764648	5.32959	5.549316	5.578613	5.412598	5.317383	5.275879	5.222168	5.15625	5.117188	5.114746	5.083008	5.041504	5.026855	5.058594	5.031738	4.995117	5.014648	5.046387	5.036621	4.975586	5.009766	5.014648	5.002441	4.975586	4.995117	5.024414
0.029297	3.039551	2.597656	1.630859	3.850098	5.32959	5.554199	5.571289	5.419922	5.310059	5.280762	5.234375	5.131836	5.100098	5.112305	5.070801	5.046387	5.031738	5.063477	5.058594	4.992676	5.002441	5.063477	5.021973	4.980469	4.995117	5.036621	5	4.960938	5.007324	5.043945
0.03418	3.186035	2.539063	1.645508	3.930664	5.351563	5.563965	5.563965	5.422363	5.307617	5.275879	5.209961	5.166016	5.095215	5.117188	5.080566	5.043945	5.036621	5.043945	5.053711	5.009766	4.997559	5.061035	5.031738	4.96582	5.004883	5.036621	5.002441	4.98291	4.985352	5.043945
0.046387	3.293457	2.495117	1.635742	4.033203	5.366211	5.549316	5.568848	5.405273	5.319824	5.253906	5.222168	5.153809	5.112305	5.102539	5.083008	5.046387	5.014648	5.061035	5.05127	4.990234	5.019531	5.05127	5.039063	4.958496	5.007324	5.031738	4.992676	4.975586	5.012207	5.03418
0.039063	3.430176	2.436523	1.650391	4.111328	5.371094	5.563965	5.563965	5.407715	5.297852	5.27832	5.214844	5.151367	5.10498	5.12207	5.075684	5.053711	5.01709	5.053711	5.039063	4.990234	5.002441	5.063477	5.024414	4.978027	5.007324	5.019531	5.002441	4.968262	5.007324	5.041504
0.041504	3.508301	2.397461	1.638184	4.189453	5.405273	5.563965	5.568848	5.390625	5.300293	5.273438	5.214844	5.144043	5.102539	5.112305	5.085449	5.039063	5.03418	5.056152	5.024414	5	5.019531	5.056152	5.024414	4.973145	5.029297	5.019531	4.990234	4.975586	4.995117	5.039063
0.043945	3.574219	2.348633	1.652832	4.284668	5.402832	5.566406	5.571289	5.373535	5.297852	5.273438	5.219727	5.129395	5.109863	5.114746	5.070801	5.043945	5.031738	5.073242	5.041504	4.975586	5.026855	5.05127	5.019531	4.98291	5.014648	5.029297	4.990234	4.970703	5.014648	5.01709
0.043945	3.601074	2.297363	1.699219	4.343262	5.427246	5.576172	5.554199	5.393066	5.292969	5.263672	5.202637	5.146484	5.10498	5.114746	5.056152	5.036621	5.043945	5.058594	5.029297	4.995117	5.012207	5.070801	4.997559	4.970703	5.019531	5.014648	4.995117	4.973145	5.009766	5.046387
0.043945	3.615723	2.272949	1.71875	4.414063	5.439453	5.563965	5.551758	5.383301	5.322266	5.253906	5.209961	5.13916	5.112305	5.12207	5.080566	5.029297	5.029297	5.065918	5.021973	4.990234	5.01709	5.048828	5.031738	4.968262	5.024414	5.026855	4.987793	4.975586	5.002441	5.039063
0.031738	3.652344	2.219238	1.779785	4.487305	5.45166	5.556641	5.544434	5.390625	5.302734	5.26123	5.209961	5.129395	5.114746	5.114746	5.065918	5.063477	5.031738	5.058594	5.031738	4.980469	5.014648	5.053711	5.019531	4.985352	5.012207	5.029297	4.987793	4.956055	5.01709	5.041504
0.043945	3.647461	2.177734	1.828613	4.536133	5.456543	5.583496	5.537109	5.371094	5.305176	5.256348	5.185547	5.13916	5.10498	5.124512	5.073242	5.041504	5.043945	5.061035	5.021973	4.987793	5	5.056152	5.021973	4.973145	5.036621	5.024414	4.995117	4.953613	5.009766	5.031738
0.046387	3.62793	2.141113	1.887207	4.594727	5.476074	5.571289	5.566406	5.36377	5.302734	5.251465	5.205078	5.134277	5.10498	5.097656	5.070801	5.048828	5.03418	5.070801	5.024414	4.990234	5.026855	5.053711	5.007324	4.978027	5.01709	5.026855	4.975586	4.975586	5.019531	5.014648
0.03418	3.623047	2.094727	1.967773	4.672852	5.456543	5.583496	5.546875	5.378418	5.288086	5.26123	5.195313	5.134277	5.124512	5.102539	5.058594	5.03418	5.053711	5.058594	5.029297	4.973145	5.021973	5.068359	4.992676	4.992676	5.036621	5.014648	4.98291	4.970703	5.019531	5.036621
0.046387	3.59375	2.062988	2.043457	4.702148	5.46875	5.578613	5.539551	5.361328	5.3125	5.253906	5.183105	5.134277	5.100098	5.126953	5.080566	5.029297	5.048828	5.073242	5.004883	4.985352	5.031738	5.05127	5.012207	4.968262	5.036621	5.004883	4.985352	4.975586	5.012207	5.026855
0.041504	3.564453	2.038574	2.109375	4.760742	5.505371	5.571289	5.534668	5.36377	5.297852	5.256348	5.197754	5.109863	5.114746	5.112305	5.063477	5.053711	5.046387	5.073242	5.002441	4.978027	5.01709	5.05127	5.002441	4.990234	5.029297	5.029297	4.98291	4.960938	5.026855	5.021973
0.036621	3.527832	1.992188	2.207031	4.814453	5.500488	5.59082	5.512695	5.373535	5.300293	5.258789	5.185547	5.102539	5.114746	5.119629	5.063477	5.029297	5.058594	5.065918	5.019531	4.987793	5.012207	5.061035	4.995117	4.985352	5.039063	5.01709	5.002441	4.960938	5.01709	5.031738
0.046387	3.464355	1.962891	2.302246	4.851074	5.512695	5.581055	5.532227	5.344238	5.302734	5.239258	5.175781	5.129395	5.112305	5.102539	5.078125	5.043945	5.043945	5.070801	5.01709	5	5.029297	5.039063	5.002441	4.973145	5.036621	5.024414	4.980469	4.975586	5.019531	5.021973
0.043945	3.415527	1.936035	2.39502	4.916992	5.505371	5.583496	5.517578	5.366211	5.302734	5.234375	5.183105	5.119629	5.12207	5.107422	5.05127	5.048828	5.046387	5.063477	5.019531	4.987793	5.019531	5.056152	4.992676	4.985352	5.014648	5.014648	4.987793	4.958496	5.026855	5.024414
0.183105	3.383789	1.90918	2.487793	4.938965	5.507813	5.598145	5.505371	5.356445	5.300293	5.256348	5.17334	5.12207	5.107422	5.114746	5.070801	5.03418	5.068359	5.053711	5.002441	4.992676	5.019531	5.048828	4.997559	4.992676	5.048828	5.007324	4.980469	4.973145	5.019531	5.024414
0.383301	3.327637	1.887207	2.568359	4.98291	5.529785	5.57373	5.512695	5.336914	5.307617	5.244141	5.17334	5.107422	5.119629	5.095215	5.070801	5.041504	5.041504	5.085449	5.002441	4.985352	5.03418	5.039063	4.995117	4.978027	5.041504	5.029297	4.970703	4.975586	5.019531	5
0.554199	3.28125	1.845703	2.670898	5.026855	5.517578	5.595703	5.500488	5.354004	5.280762	5.249023	5.185547	5.10498	5.124512	5.10498	5.05127	5.036621	5.048828	5.065918	5.014648	4.995117	5.024414	5.046387	4.973145	4.995117	5.046387	5.012207	4.990234	4.975586	5.03418	5
0.732422	3.210449	1.828613	2.773438	5.043945	5.537109	5.595703	5.495605	5.341797	5.280762	5.239258	5.170898	5.119629	5.10498	5.10498	5.058594	5.01709	5.053711	5.075684	5	4.997559	5.03418	5.048828	4.968262	4.987793	5.036621	5.01709	4.970703	4.980469	5.01709	5.01709

SIMULATION OF PROCESS CONTROL VALVE STICTION

S. Sewdass[1] and P. Govender[2]

Department of Electronic Engineering,

Optimisation and Energy Studies Unit,

Durban University of Technology,

KwaZulu Natal, South Africa

Email: 1. sugiths@dut.ac.za; 2. poobieg@dut.ac.za

ABSTRACT

Control valves are usually the main source of problems in a control loop. The poor performance of a control valve impacts negatively on the performance of a loop during a control session, and this can have a negative impact on production. Regular monitoring of the health and performance of control valves are important as it can eliminate the possibility of breakdown and unplanned plant shutdown caused by a poorly performing control valve. This paper presents a new method for simulation of stiction in process control valves. The proposed method investigates the modification of the cam of a pneumatic positioner in order to simulate stiction. Closed loop tests are used to confirm the presence of valve stiction.

KEYWORDS: Control valve, stiction, simulation

1. INTRODUCTION

Nonlinearities in process control valves have a major effect on the performance of a process control loop. Deadband, stiction, positioner overshoot and are regular sources of nonlinearities in process control valves. The most severe and common nonlinearities in process control valves are static friction (stiction) and hysteresis [1]. There have been many different views on the definition of stiction. From [2], “Stiction is a property of an element such that its smooth movement in response to a varying input is preceded by a sudden abrupt jump called the slip-jump. Slip-jump is expressed as a percentage of the output span. Its origin in a mechanical system is static friction which exceeds the friction during smooth movement.” The phase plot describing the input- output behaviour of a valve experiencing stiction is shown in Figure 1 [2], [4]. With regard to Figure 1, we have four regions: dead band, stickband, slip jump and the moving phase (A-G and E-D). The valve will stick when it comes to rest or changes direction at point A. The valve jumps to position D once the controller output overcomes the deadband (AB) and the stickband (BC), and thereafter continues to move past position D. Due to very low or zero velocity, the valve may stick again in between points D and E whilst travelling in the same direction. Stiction results in limit cycling and compromises the closed-loop stability of the process.

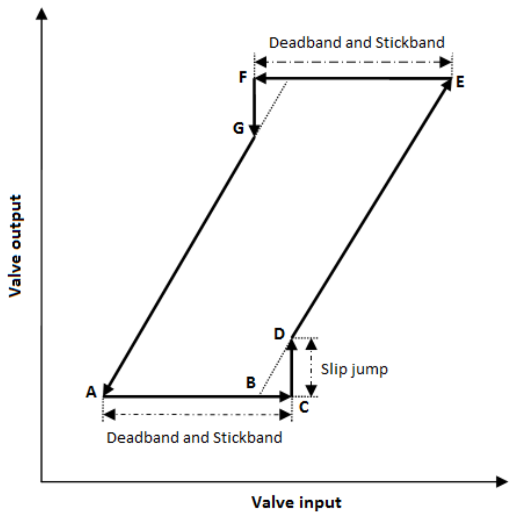


Figure 1: Input- output behaviour of a sticky valve [2]

2. GENERAL OVERVIEW OF STICTION MODELLING

The two methods used to model stiction are the data driven model and the physical model. Several examples of stiction exist in the literature, cf. [7], [8], such as a physical model similar to the Karnopp model which is based on a force balance system implemented in Simulink [7] , [8]. Physical models of stiction require parameters such as the valve frictional force, static friction, and valve stem mass, spring constant and actuator air pressure. These parameters are difficult to obtain as they rely on the empirical experience of the practitioner. Data dependent models quantify stiction as a percentage of valve travel or span of the input signal [2]. The data driven model utilises two parameters from plant data, namely the valve dead band, plus the stick band with its associated slip-jump. Choudhury [20] applied Newton's second law to model static friction to derive a data driven approximate model of stiction (1).

$$\mathrm{M_s}\ddot{x}_s = \sum_i \mathrm{Fi} = \mathrm{F_a} + \mathrm{F_r} + \mathrm{F_f} + \mathrm{F_p} + \mathrm{F_j} \qquad (1)$$

With regards to (1), M is the mass of the moving body and x is the relative stem position; $\mathrm{F_a}$ denotes the force applied by the pneumatic actuator and $\mathrm{F_r} = -kx$ represents the spring force where k is the spring constant. F_f , F_p and F_j are the forces due to frictional force, pressure and an additional force required to shift the valve into its seat, respectively [2]. From [2], $\mathrm{F_f}$ can be expressed by (2):

$$F_f = \begin{cases} -F_c sgn(\dot{x}) - \dot{x}F_v \quad if\ x \neq 0 \\ -(F_a + F_r)\ if \dot{x} = 0\ and |F_a + F_r| \leq F_s \\ -F_s sgn(F_a + F_r)\ \ if \dot{x} = 0\ and |F_a + F_r| > F_s \end{cases} \tag{2}$$

Where F_c is coulomb friction, F_v indicates the viscous friction and F_s denotes the maximum static friction that must be overcome for valve movement.

2.1. Review of Methods to confirm stiction

A direct test to detect stiction is possible by comparing PV to the controller's output signal (OP) for determining the valve's slip characteristics curve[6];[7]. Horch [9] proposed a very simple method based on a cross correlation between CO and PV. Rengaswamy [10] uses a neural network to approximate the process output by means of seven different elementary shapes (primitives), and associating square and triangular waves to the presence of stiction. [7]; [10]. Gerry and Ruel [11]-[13] detected valve stiction by manually inspecting the shapes of the controller output signals during sustained oscillation. The controller output would be a saw tooth wave and the PV would be a square wave for a sticky valve. The method of [11]-[13] is a practical method to determine valve stiction and is extensively applied in the process control industry.

3. PROPOSED METHOD

Stiction usually occurs when a valve's packing is over-tightened during a maintenance cycle. In this study, the electro- pneumatic valve positioner YT-1000R is used to position a pneumatic butterfly valve via a pneumatic actuator. The positioner cam is attached to the positioner feedback shaft and the rotary actuator main shaft. The configuration of the position of the cam on the positioner's feedback shaft determines whether the valve is reverse acting or direct acting. The cam is part of the positioner that influences the stroke of the actuator.

The control valve's inherent characteristic can be adjusted by altering the cam. For this study, the obstruction shown in Figure 2a was placed on the cam in order to alter the valve characteristic and hence simulate valve stiction. Bearing movement in a clockwise direction along the cam is hindered by this obstruction. Valve motion occurs till the bearing reaches the obstruction. At the point of obstruction, the valve will remain stationary until the controller output overcomes the stick band of the valve. The valve then moves abruptly to the new position as a result of the build-up of pressure in the actuator. The valve experiences a similar slip jump phenomenon when returning to the closed position.

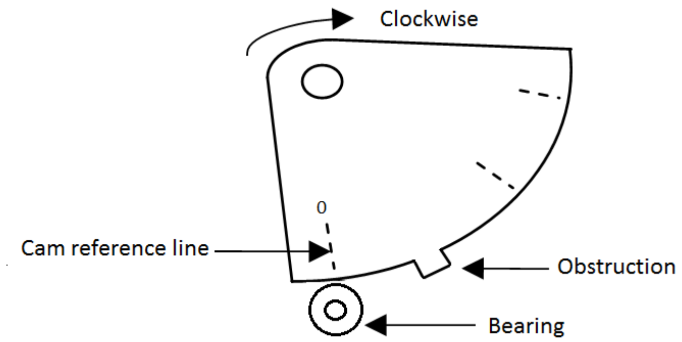


Figure 2a: Cam with modification

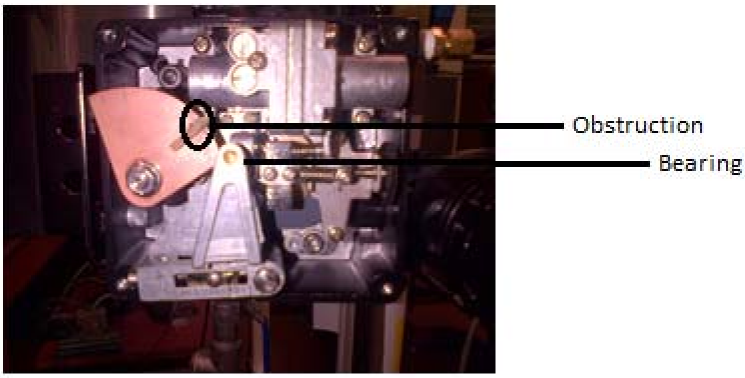


Figure 2b: Cam with modification

3.1. Analysis of Results and Conclusion

A tuned PI control loop was used to obtain the closed loop response. When stiction occurs, the output from the PI controller ramps up until the force is big enough to overcome the static frictional forces and the valve then moves to its new position. From Figure 3, we observe that stiction induces a limit cycle with a characteristic saw tooth shape in the controller output and a square wave in the PV. The limit cycling of the PV is due to the offset between the set point and PV. Figure 4 shows the elliptical trajectories with a flat region and sharp turn-around points. The flat region is due the valve's dead-band combined with its stickband [9], [15].

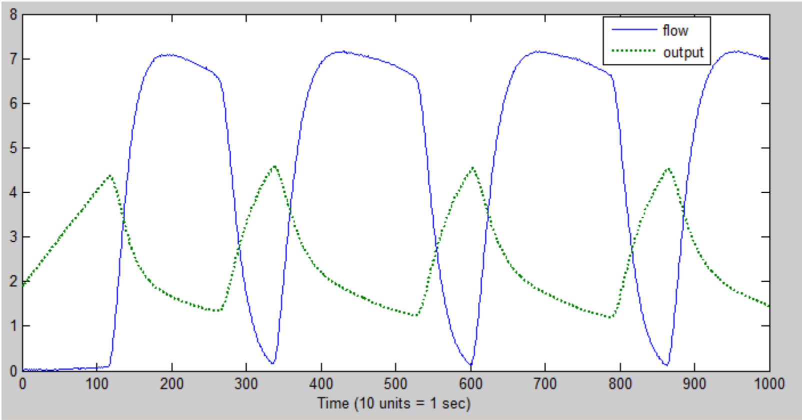


Figure 3: Closed loop response

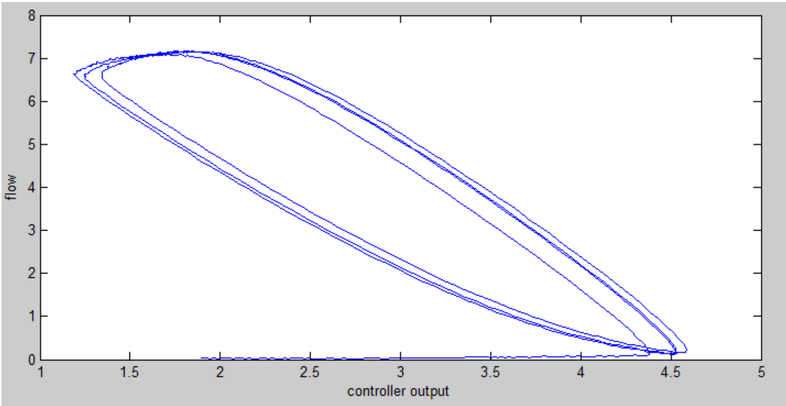


Figure 4: Process variable *versus* controller output

The impact of the stiction on the closed-loop performance varies linearly with the size of the cam obstruction. Figure 5a to Figure 6b shows the impact of the changes to the cam's characteristics on the closed-loop performance and these results confirms those of [10], [17], and [18]. From Figure 5a to Figure 6b, we observe the following:

- Oscillation amplitude increases with stiction size because of increased CO.
- Dead zone size increases with stiction (cf. db1 and db2 on Figure 5a and Figure 6a, respectively).

- Limit cycle frequency reduces when stiction increases due to the larger dead-band plus stickband (cf. Pb1< Pa1 and Pb2 < Pa2 on Figure 5a and Figure 6a, respectively).

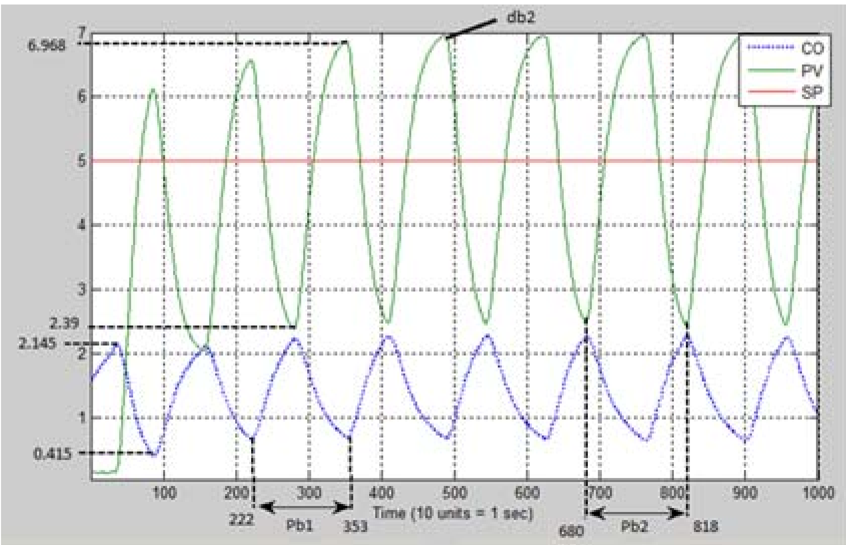


Figure 5a: Closed loop response (low stiction)

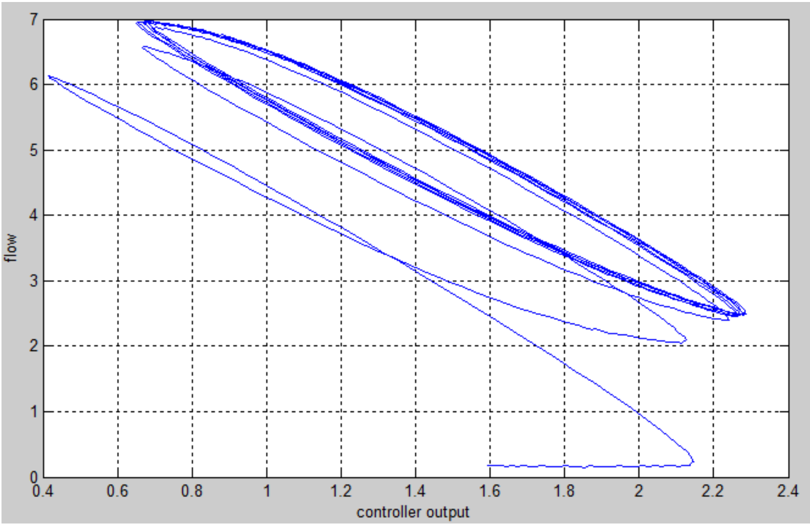


Figure 5b: Closed loop response (low stiction)

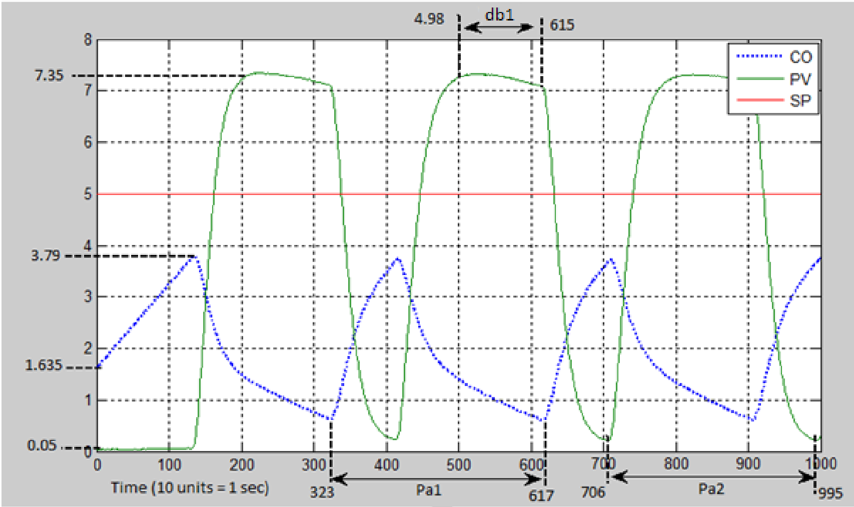


Figure 6a: Closed loop response (increased stiction)

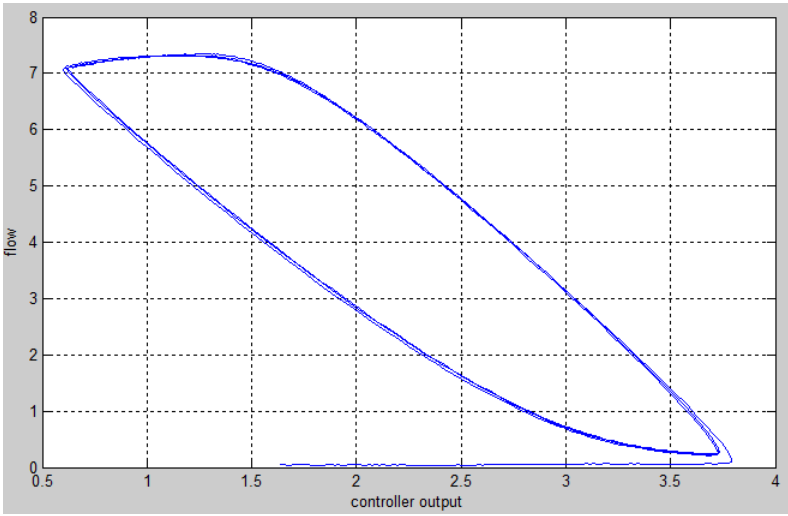


Figure 6b: Closed loop response (increased stiction)

From the previous discussions our proposed technique to simulate control valve stiction eliminates the need to create complex models for analysis purposes. Our method allows for closed-loop stability analysis and the investigation of stiction compensation methods under dynamical conditions.

REFERENCES

[1] T. Hagglund, *Stiction compensation in control valves, In European Control Conference, Brussels, Belgium, 1997.*

[2] M.A.A Shoukat Choudhury, *Modeling valve stiction*, Control Engineering Practice 13 (2005) 641–658.

[3] Horch, A., A. J. Isaksson and K. Forsman, *Diagnosis and characterization of oscillations in process control loops*, In: Proceedings of the Control Systems, Victoria Canada (2000) 161–165.
[4] EnTech, *Control valve dynamic specification* (1998), (version 3.0).
[5] S. Sivagamasundari and D. Sivakumar, *A practical Modelling Approach for stiction in control valves*, In Procedia Engineering Volume 38, 2012, Pages 3308–3317.
[6] M. A. A. S. Choudhury, N. F. Thornhill and S. L. Shah, *A Data-Driven Model for Valve-Stiction*, to appear in ADCHEM Hong Kong, 2004 Jan 11-14.
[7] M. Rossi and C. Scali, *A comparison of techniques for automatic detection of stiction: simulation and application to industrial data*, Journal of Process Control 15,505-514.
[8] D. Karnoop, *Computer simulation of stick-slip friction in mechanical dynamic systems*, ASME J. of Dynamic Systems, Measurements and Control, vol. 107, no. 1, 1985, pp.100-103.
[9] A. Horch& A. J.Isaksson, *Detection of valve stiction in integrating processes*, European control conference, Porto (Portugal) (2001), pp. 1327–1332.
[10] R. Rengaswamy, T. Hägglund, V. Venkatasubramanian, *A qualitative shape analysis*] *formalism for monitoring control loop performance*, Engineering Applications of Artificial Intelligence, 14 (2001), pp. 23–33
[11] M. Ruel, *Valve diagnosis identifies process problems*, in: Proc. ISA Western Regional Conf. and Exhibition, Las Vegas, NV, 2002.
[12] J. Gerry, M. Ruel, *How to measure and combat valve stiction on line*, in: Proc. ISA2001, Instrumentation, Systems and Automated Society, Houston, TX, 2001.
[13] A. Singhal and T. I. Salsbury, *A simple method for detecting valve stiction in oscillating control loops*. Journal of Process Control, 15 (4):371–382, 2005.
[14] Control valve positioned cam characteristics, (11-08-15), http://instrumentation.web.id]
[15] M. Jelali and B. Huang, *Detection and Diagnosis of Stiction in Control Loops State of the Art and Advanced Methods*, (2010), Chapter 2, ISBN: 978-1-84882-774-5.
[16] YT-1000 series data sheet.
[17] M.A.A.S. Choudhury, Jain M., Shah S.L., Shook D.S., *Stiction - definition, modelling, detection and quantification*, Journal of Process Control, (2008), 18, 232-243.
[18] R.A. Romano, C. Garcia, *Karnopp Friction model identification for a real control valves*, Proceedings of the 17th IFAC World Congress, IFAC'08, Seoul, Korea, July 6-11, 2008.
[19] S. Sivagamasundari, D. Sivakumar, *A new methodology to compensate stiction in pneumatic control valves*, Journal: International Journal of Soft Computing & Engineering ISSN/EISSN: 22312307, (2013) Volume: 2 Issue: 6 Pages: 480-484
[20] M. A. A. S. Choudhury, N.F. Thornhill, and S.L. Shah,*Modelling valve stiction,Control Engineering Practice, 12:641–658,(2005)*
[21] M. A. A. Shoukat Choudhury; Vinay Kariwala; Sirish L. Shah; Hisato Douke; Haruo Takada; Nina F. Thornhill, *A simple test to confirm control valve stiction, IFAC World Congress 2005, July 4-8, Praha*

Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

CONTROL VALVE STICKBAND COMPENSATOR

S. Sewdass, N. Pillay, K.E. Moorgas, P. Govender*

Department of Electronic Engineering,
Optimisation and Energy Studies Unit,
Durban University of Technology,
KwaZulu Natal, South Africa
*Email:*poobieg@dut.ac.za*

Abstract: Control valve stiction is a common problem experienced by process control loops and is one of the main causes of loop cycling during a control session. This paper proposes a simple effective stickband compensator which was applied to a plant for reducing stickband and limit cycle amplitude within a unity feedback system. The technique is based on a 'stickband-jacket' applied across the input and the output of the actual control valve. The feedback error signal is used to vary the width of the stickband and limit cycle frequency. The compensator adds a single increment to the controller's degree-of-freedom and can be easily added to any existing control loop.

Keywords: Control valve, stiction, stickband, limit cycle, compensator

1. INTRODUCTION

Nonlinearities in process control valves have a major effect on the performance of a process control loop. Deadband, stiction, positioner overshoot are regular sources of nonlinearities in process control valves. The most severe and common nonlinearities in process control valves are static friction (stiction) and hysteresis (Hagglund, 2002). There have been many different views on the definition of stiction. From (Choudhury, 2005), "Stiction is a property of an element such that its smooth movement in response to a varying input is preceded by a sudden abrupt jump called the slip-jump. Slip-jump is expressed as a percentage of the output span. Its origin in a mechanical system is static friction which exceeds the friction during smooth movement." The phase plot describing the input- output behaviour of a valve experiencing stiction is shown in Fig. 1 (Choudhury, 2005a), (Entech, 1998). With regard to Fig. 1, we have four regions: dead band, stickband, slip jump and the moving phase (A-G and E-D). The valve will stick when it comes to rest or changes direction at point A. The valve jumps to position D once the controller output overcomes the deadband (AB and the stickband (BC), and there after continues to move past position D. Due to very low or zero velocity, the valve may stick again in between points D and E whilst travelling in the same direction. Stiction results in limit cycling and compromises the closed-loop stability of the process.

2. GENERAL OVERVIEW OF STICTION MODELLING

The two methods used to model stiction are the data driven model and the physical model. Several examples of stiction exist in the literature (Karnopp, 1985; Rossi and Scali, 2005), such as a physical model similar to the Karnopp model which is based on a force balance system implemented in Simulink. Physical models of stiction require parameters such as the valve frictional force, static friction, and valve stem mass, spring constant and actuator air pressure. These parameters are difficult to obtain as they rely on the empirical experience of the practitioner. Data dependent models quantify stiction as a percentage of valve travel or span of the input signal (Choudhury, 2005a).The data driven model utilises two parameters from plant data, namely the valve dead band, plus the stick band with its associated slip-jump.

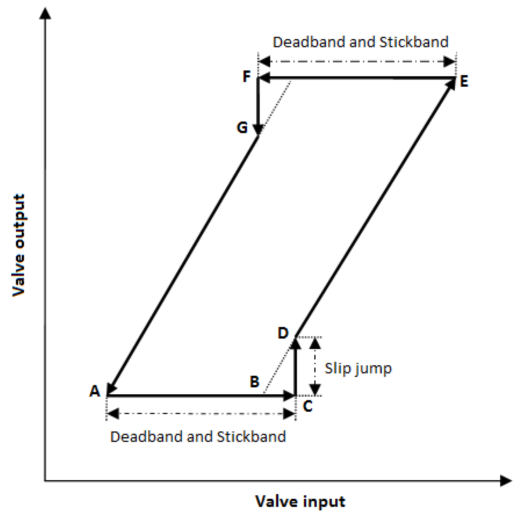


Fig.1. Input- output behaviour of a sticky valve (Choudhury, 2005a)

Choudhury (2005b) applied Newton's second law to model static friction to derive a data driven approximate model of stiction (1).

$$M\ddot{x}(t) = \sum\left(F_a(t), F_r(t), F_f(t), F_p(t), F_j(t)\right) \qquad (1)$$

With regards to (1), M is the mass of the moving body and x is the relative stem position; F_a denotes the force applied by the pneumatic actuator and $F_r = -kx$ represents the spring force where k is the spring constant. F_f, F_p and F_j are the forces due to frictional force, pressure and an additional force required to shift the valve into its seat, respectively (Choudhury, 2005a). F_f can be expressed by (2):

$$F_f = \begin{cases} -F_c sgn(\dot{x}) - \dot{x}F_v \quad if\ x \neq 0 \\ -(F_a + F_r)\ if\ \dot{x} = 0\ and |F_a + F_r| \leq F_s \\ -F_s sgn(F_a + F_r)\ if\ \dot{x} = 0\ and |F_a + F_r| > F_s \end{cases} \qquad (2)$$

F_c is coulomb friction, F_v indicates the viscous friction and F_s denotes the maximum static friction that must be overcome for valve movement (Choudhury, 2005a).

2.1. Plant overview

The plant used in the study is given in Fig.2. The signalling conditions are shown in Table 1. An electro-pneumatic valve positioner is used to position a pneumatic butterfly valve via a pneumatic actuator. The cam is part of the positioner that influences the stroke of the actuator as shown in Fig.3. An obstruction was placed on the cam in order to alter the valve characteristic for simulating valve stiction.

2.2. Review of Methods to confirm stiction

A direct test to detect stiction is possible by comparing PV to the controller's output signal (CO) for determining the valve's slip characteristics curve (Gerry and Ruel, 2001; Singal and Salsbury, 2005; Rossi and Scali, 2005). CO is a saw tooth wave and the PV is square for a sticky valve as shown in Fig. 4. The method of comparing PV to CO is a practical method used by control practitioners to detect stiction. Horch (2001) proposed a method based on a cross correlation between CO and PV. From the correlation plot in Fig. 5, the flat region of nonlinearity indicates the valve's stickband. Rengaswamy *et al.* (2001) applied an artificial neural network to detect stiction by associating square and triangular waves to the presence of stiction. Fig. 5 and Fig. 6 shows the impact of varying degrees of stiction which confirms the results of (Rengaswamy, 2001), (Choudhury, 2008) and (Romano, 2008).

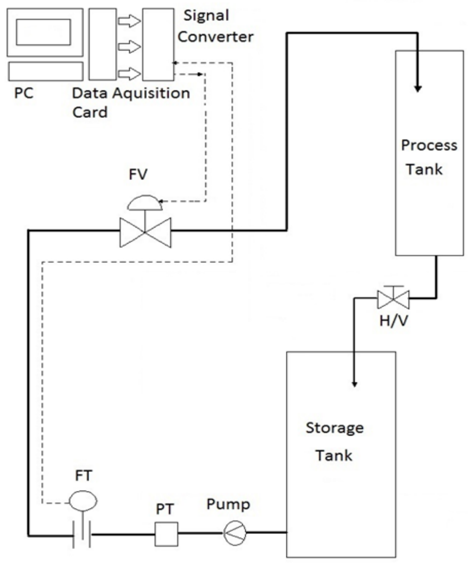


Fig.2. Plant

Table 1. Loop signals

CO	V	mA
0	0	4
2.5	2.5	8
5	5	12
7.5	7.5	16
10	10	20

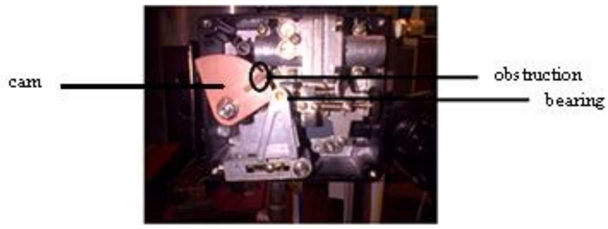


Fig.3. Cam with modification

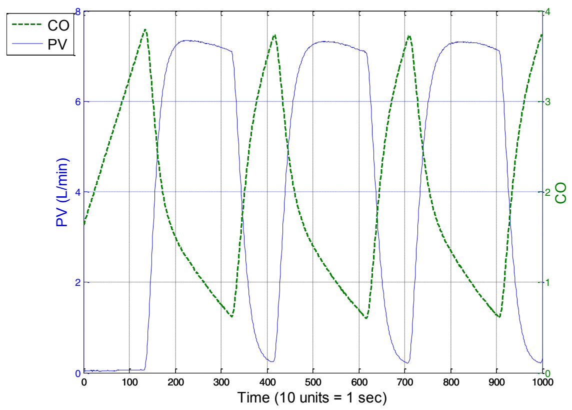


Fig. 4. Closed loop response with stiction present

From Fig. 5 and Fig. 6 we observe the following:

- Cycling amplitude increases with stiction size due to an increased CO.
- Dead zone size increases with stiction.
- Limit cycle frequency reduces with stiction increases.

3. STICTION COMPENSATION

3.1. Stiction compensation methods

Hagglund's knocker (2002) utilises knocker pulses as a additive to CO for overcoming stiction. Kayihan and Doyle (2000) proposed a stiction compensator based on the control valve's operating parameters. The drawback of both methods is the increased stem movement that leads to an increased rate of valve deterioration (De Souza *et. al*, 2012). Many other stiction compensation methods are widely available in the literature.

3.2. Proposed Stickband compensation method

The stickband compensator device proposed in this paper is based on Glattfelder's and Schauffelberger's (1986) technique where an 'anti-windup jacket' is placed around the model of the saturation nonlinearity in order to minimise the effect of the nonlinearity on the loop's behaviour during a control session. Glattfelder and Schauffelberger's (1986) technique reduces the impact of integral windup which occurs when the integral controller calls for a control action that the valve is not capable of producing, usually during plant start-up and load changes. This results in limit cycling and overshoots in process variable. We have applied this technique to reduce the width of the stickband in control loops experiencing stiction nonlinearity.

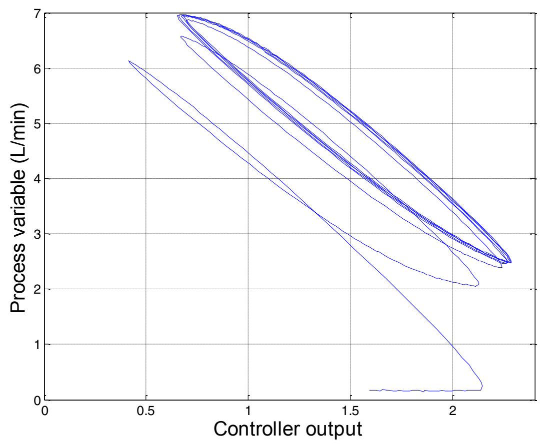


Fig. 5. Correlation plot for weak stiction

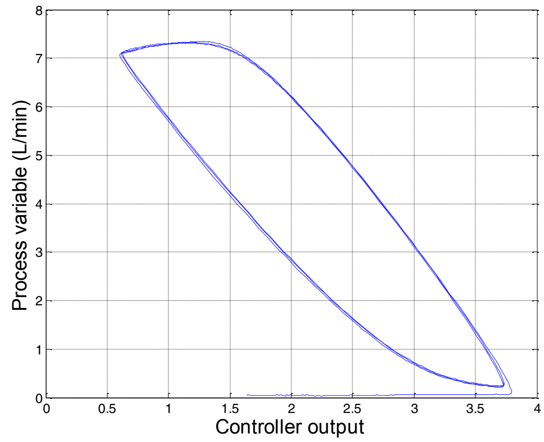


Fig. 6. Correlation plot for strong stiction

The schematic of the 'stickband compensator' is given in Fig. 7, where the feedback from the so-called 'stickband-jacket' is used to create an additional feedback signal for the integral controller. With regards to Fig. 7, the output of the controller (u_c) is compared to the input signal to the process (u'_c) to yield the stiction error (e'). The compensator gain Ks is used to vary the width of the stickband within its upper and lower bands.

3.1 Control loop with the stickband compensator

The compensator is included in the topology of a Type 1 PI/ PID controller and the governing algorithms are defined as follows:

$$U_{PI}(t) = K_p e(t) + \int_{t0}^{tf} [K_i e(t) - K_s(u_c - u_c')]dt = K_p e(t) + \int_{t0}^{tf} [K_i e(t) - K_s e'(t)]dt \tag{3}$$

$$U_{PID}(t) = K_p e(t) + \int_{t0}^{tf} [K_i e(t) - K_s e'(t)]dt + K_d e(t)dt \tag{4}$$

Equations 3 and 4 are based on the ideal PID algorithm. With regards to equation 3, u_c is the controller output, u'_c denotes the output from the valve and e(t) represents the instantaneous error signal; K_p, K_i and K_d represent the gains of the proportional, integral and derivative controller, respectively; K_S denotes the gain of the stick-band compensator. Utilising Ks in the feedback loop shifts the control from 1-degree of freedom (DOF) to 2-DOF. The loop response converges faster for increases in Ks, with increased oscillations; the opposite applies when K_S is reduced. The impact of K_S on loop behaviour is described by (5).

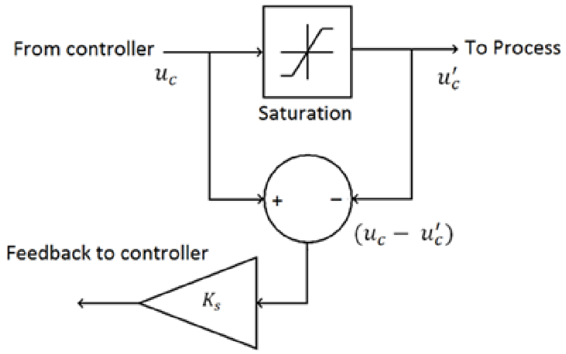


Fig. 7. Stickband compensator

$$K_s = \begin{cases} >1 & \text{high oscillation frequency with reduced stickband} \\ <1 & \text{increased stickband with low oscillating frequency} \\ 1 & \text{optimal setting} \\ 0 & \text{zero compensation} \end{cases} \tag{5}$$

4. DISCUSSION OF RESULTS

The response of the plant where the stickband compensator was applied is shown in Fig. 8. With regards to Fig. 8, the stick-band is substantially reduced when the compensator is applied. The amplitude of the oscillations is reduced but is accompanied by an increase in limit cycle frequency. D-action substantially reduces the oscillation amplitude, whilst P-only control eliminates the oscillation and stickband, but yields poor servo tracking.

By limiting the amplitude of the oscillation, the net impact of the compensator is to maintain loop operation within the *(-1+j0)* region of the Nyquist plot, hence ensuring stable gain and phase margins

5. ANALYSIS AND CONCLUSION

The closed-loop correlation plots for PI and PID control is shown in Fig. 9 to Fig. 13.

1. The compensator reduces the width of the stick-band and limit cycle amplitude (cf. Fig.9 *vs* Fig.10 and Fig. 11). Reduced amplitude is brought about by a decrease in the valve's kinetic and potential energies.
2. The reduction in the PV and CO is due to the compensator's internal feedback limiting the integral action at saturation (cf. Fig.10 and Fig. 12).
3. With regards to Fig. 13: For only P-only control and with no compensation present we observe that the response does not have any limit cycling. This also holds true for the response without the compensator. The cost though is poor servo tracking
4. The compensator reduces product wastage and saves energy.

The stiction compensator reduced stickband width without totally eliminating the source of the valve stiction. P-only control with the stiction compensator displays promising results, but achieving the setpoint remains a challenge. The research is currently in progress and potential solutions are being investigated. To eliminate the stiction, the valve will have to be removed from production during scheduled maintenance and the stiction contributors such as the packing and valve lining within the valve assembly must be attended to.

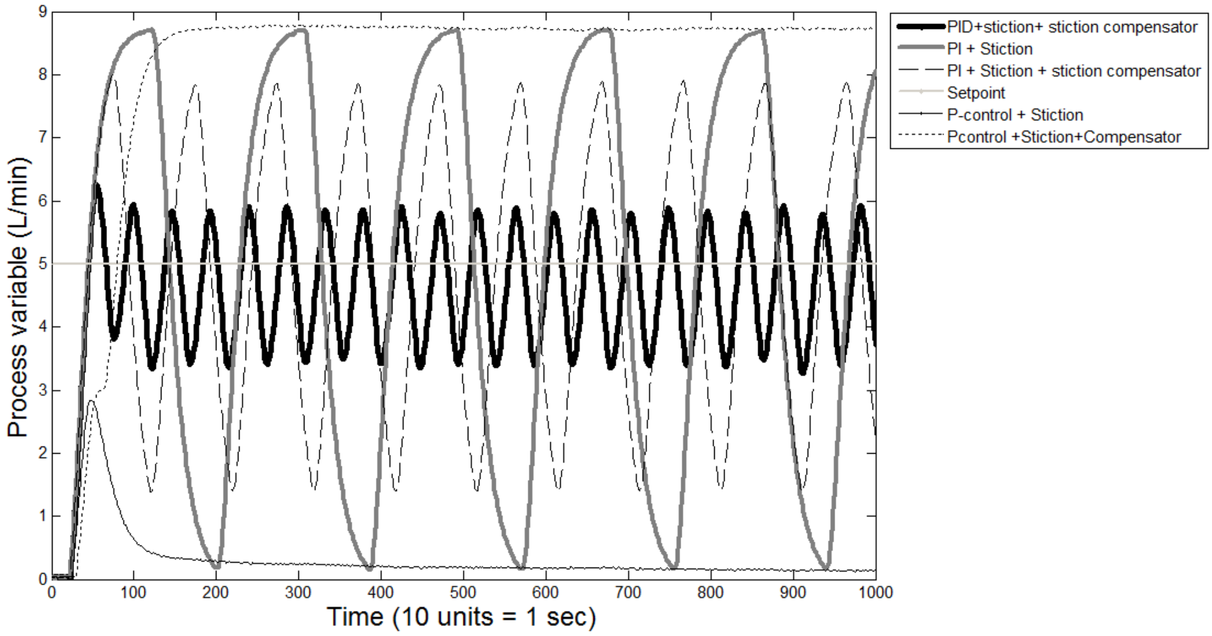


Fig. 8. Plant response with stickband compensator

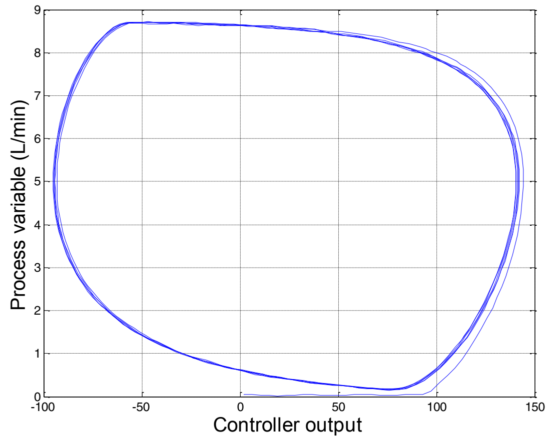


Fig. 9. Correlation with PI control without stickband compensator.

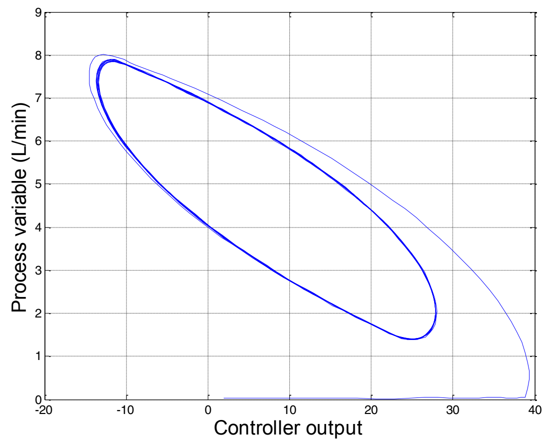


Fig. 10. Correlation with PI control with stickband compensator.

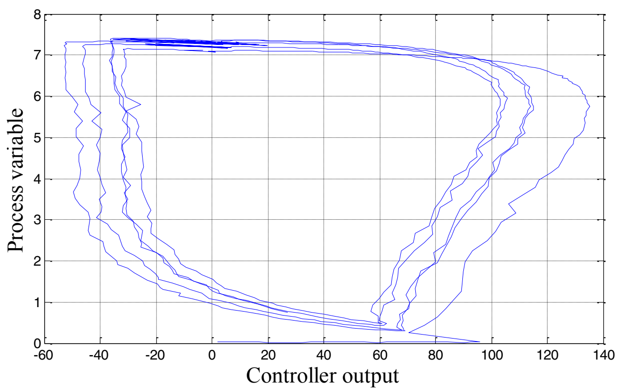


Fig. 11. Correlation with PID control and no stickband compensator.

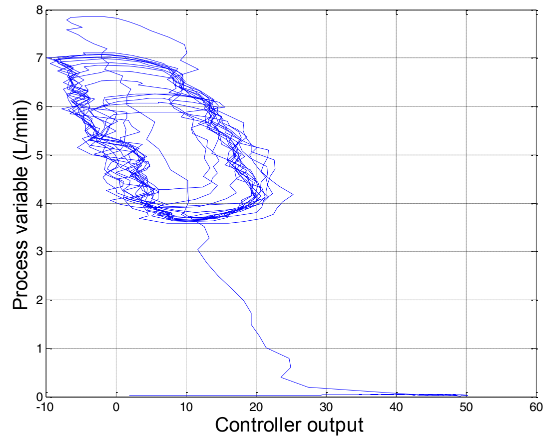


Fig. 12. Correlation with PID control and stickband compensator.

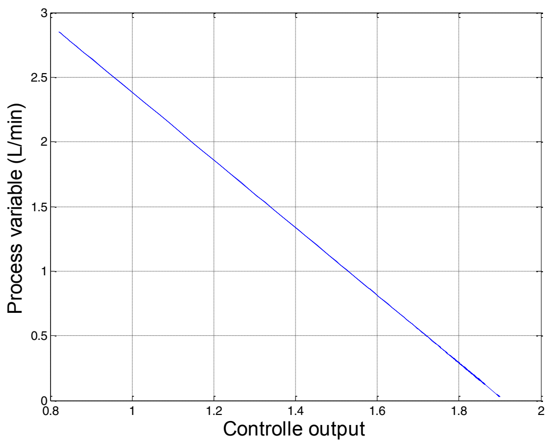


Fig. 13. Correlation for P-control and stiction compensator.

REFERENCES

Choudhury, M.A.A. S. (2005a). Modelling valve stiction, *Control Engineering Practice*, volume (13), pp. 641–658.

Choudhury, M. A. A. S. , N. F. Thornhill and S. L. Shah, (2004 Jan 11-14). A Data-Driven Model for Valve-Stiction, In a proceedings volume from the*IFAC Symposium on Advanced Control of Chemical Processes (ADCHEM)*, Hong Kong. Volume (1), pp.245-250

Choudhury, M.A.A.S., Jain M., Shah S.L., Shook D.S. (2008). Stiction - definition, modelling, detection and quantification, *Journal of Process Control*, volume (18), pp. 232-243.

Choudhury, M. A. A. S., Vinay Kariwala, Sirish L. Shah; Hisato Douke; Haruo Takada; Nina F. Thornhill, (2005b). A simple test to confirm control valve stiction, *Proceedings of the 16th IFAC World Congress, Praha*, volume (16), pp.1588-1588

De Souza, Marco Antonio, Cuadrosa, L., Munarob, C.J., and Munaretoa S. (2012). Improved stiction compensation in pneumatic control valves. Computers and Chemical Engineering, volume (38), pp. 106-114

EnTech, (1998). Control valve dynamic specification (version 3.0).Available at http://www.emersonprocess.com/entechcontrol/download/publications/.

Glattfelder A.H., and W. Schaufelberger, (1986). Start-up Performance of Different Proportional-Integral-Anti-Windup Regulators. *Int. J. Control*, Volume (44), No.2, pp.493-505.

Gerry, J. and Ruel, M. (2001). How to measure and combat valve stiction on line, in: *Proc. ISA2001, Instrumentation, Systems and Automated Society, Houston, TX*. Available at http://www.expertune.com/articles/isa2001/StictionMR.htm.

Hägglund, T. (2002), A Friction Compensator for Pneumatic Control Valves, J. Process Control 12, 897–904

Horch, A. &Isaksson, A.J. (2001) Detection of valve stiction in integrating processes, *European control conference, Porto (Portugal)*, pp. 1327–1332.

Karnoop, D. (1985). Computer simulation of stick-slip friction in mechanical dynamic systems, *ASME J. of Dynamic Systems, Measurements and Control,* volume (107), pp.100-103.

Kayihan, A. & Doyle, F. J., III. (2000). Friction compensation for a process control valve. *Control Engineering Practice*, volume (8), pp. 799–812.

Rengaswamy, R. Hägglund, T. and Venkatasubramanian, V. (2001). A qualitative shape analysis] formalism for monitoring control loop performance, *Engineering Applications of Artificial Intelligence*, volume(14), pp. 23–33

Ruel, M. (2002). Valve diagnosis identifies process problems, In: *Proc. ISA Western Regional Conf. and Exhibition, Las Vegas,NV*, Available at http://www.topcontrol.com/en/papers.htm.

Romano, R.A. and Garcia, C. (2008). Karnopp Friction model identification for a real control valves, *Proceedings of the 17th IFAC World Congress, Seoul, Korea, volume (17), pp.14906-14911*

Rossi, M. and Scali,C. (2005). A comparison of techniques for automatic detection of stiction: simulation and application to industrial data, *Journal of Process Control* volume (15), pp. 505-514.

Singhal, A. and T. I. Salsbury, T. L. (2005). A simple method for detecting valve stiction in oscillating control loops. *Journal of Process Control*, volume 15 (4), pp. 371–382.