

**CONTROLLER PERFORMANCE OF P, PI AND NEURAL NETWORK
CONTROL IN VINYL ACETATE MONOMER PROCESS**

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BORANG PENGESAHAN STATUS TESIS

JUDUL: CONTROLLER PERFORMANCE OF P, PI AND NEURAL NETWORK CONTROL
IN VINYL ACETATE MONOMER PROCESS

SESI PENGAJIAN: 2007/2008

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**CONTROLLER PERFORMANCE OF P, PI AND NEURAL NETWORK
CONTROL IN VINYL ACETATE MONOMER PROCESS**

FAIZAL NAZARETH IBRAHIM

**A thesis submitted in fulfillment of the
requirements for the award of the degree of
Bachelor of Chemical Engineering**

**Faculty of Chemical & Natural Resources Engineering
University Malaysia Pahang**

May, 2008

I declare that this thesis entitled “Controller Performance of P, PI and Neural Network Control in Vinyl Acetate Monomer Process” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any degree.

Signature :

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Date :

*In the Name of Allah, Most Gracious, Most Merciful.
All praise and thanks are due to Allah Almighty and peace and blessings be upon His
Messenger.*

To mum and dad, thanks for the love and support.

ACKNOWLEDGEMENT

First of all, I feel grateful to Allah s.w.t for giving me strength and good health in order to complete this thesis. I also would like to convey my thankful to my supervisor, Miss Rohaida bte Che Man for her help and guidance for this thesis. Not forgotten big thanks and grateful to my co-supervisor and also my panel Encik Noor Asma Fazli Abdul Samad for being my personal navigator who always gives me courage and his kindness on delivering me his knowledge on writing the thesis. With only their professional help and guidance make this thesis completely finish.

Besides that, I also would like to dedicate my appreciation to all my lecturers in the Faculty of Chemical Engineering and Natural Resources (FKKSA) for their support and motivation during this project development. Their view, advice and opinion really help and contribute to my understanding for this thesis.

Thanks for all my colleagues that have support me a lot and their assistance along the development of this thesis. Their kind and tips are useful indeed. And lastly to my beloved parent and family for being my inner strength all the time.

ABSTRACT

This research is about investigating the controller performance between P, PI and Neural Network control in Vinyl Acetate Monomer (VAc) Process. The manufacturing process is about vapor-phase reaction converting ethylene (C_2H_4), oxygen (O_2) and acetic acid (HAc) into vinyl acetate (VAc) with water (H_2O) and carbon dioxide (CO_2) as byproducts. The data from the process are successfully generated and the simulation of the dynamic response is done with further analysis of P, PI control and Neural Network control. The study is focusing on the column section process as the clear view of the control performance is observed. The Proportional (P) and Proportional Integral (PI) control are type of controller that used in the process. The Neural Network control then is a control mechanism that has the similar system of human neurons for processing information data. It consists of network of neurons that have weight in each network and built generally in layers. As the analysis result of P and PI control showed that there are some unsatisfying results, Neural Network Control is then developed to see the changes. In Neural Network control, the data has been trained and validate to get the better response before applied again to the process to see the improvement. At the end, Neural Network has visualized the better control performance as the unsatisfying response of P and PI control have been improvised.

ABSTRAK

Kajian ini adalah untuk mempelajari perbezaan prestasi antara kawalan PID dan kawalan Hubungan Neural dalam contoh kes daripada proses penghasilan Vinyl Acetate. Proses reaksi fasa gas ini menghasilkan Vinyl Acetate (VAC) daripada ethylene (C_2H_4), oksigen (O_2) dan asid asetik (HAc) dan air (H_2O) serta karbon dioksida (CO_2) sebagai produk sampingan. Data daripada proses ini telah ditafsir keluar dengan baik dan simulasi dinamik respon dilakukan beserta analisis kontrol P dan PI dan juga kontrol hubungan neural. Kajian ini juga difokuskan pada bahagian proses pengasingan kolum untuk pemerhatian yang lebih jelas kepada prestasi kawalan. Kawalan P dan PI adalah kawalan yang digunakan di dalam proses ini. Kawalan Hubungan Neural pula adalah kawalan yang mirip kepada system tranformasi maklumat neurons manusia. Ianya mengandungi jaringan neuron dan berat tersendiri oleh setiap jaringan hubungan itu. Oleh kerana hasil analisis daripada kawalan P dan PI telah menunjukkan hasil yang kurang memuaskan, kawalan neural telah diimplimentasikan untuk melihat sebarang perubahan. Pada akhir kajian, kawalan neural telah menunjukkan bahawa hasil kawalan itu dapat diperbetulkan dan seterusnya melihatkan keberkesanan kawalan neural berbanding kawalan P dan PI.

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LIST OF SYMBOLS

SYMBOLS / ABBREVIATION	TITLE
m	Manipulated variable
d	Potential disturbance
y	Output
y_m	Measured value
y_{sp}	Set point value
ϵ	Deviation error
G_p	Process
G_d	Disturbance
G_m	Measurement
G_c	Controller
G_f	Final Control Element
K_c	Gain
K'_p & K'_d	Closed-loop static gains
t	Time constant
t_d	Dead time

CHAPTER 1

INTRODUCTION

1.1 Introduction

In 1998, an additional model of a large, industrially relevant system, a vinyl acetate monomer (VAC) manufacturing process, was published by Luyben and Tyreus. The VAC process contains several standard unit operations that are common to many chemical plants. Both gas and liquid recycle streams are present as well as process-to-process heat integration. Luyben and Tyreus presented a plantwide control test problem based on the VAC process. The VAC process was modeled in TMODES, which is a proprietary DuPont in-house simulation environment, and thus, it is not available for public use (Luyben and Tyreus, 1998).

The model of the VAC process is developed in MATLAB, and both the steady state and dynamic behavior of the MATLAB model are designed to be close to the TMODES model. Since the MATLAB model does not depend on commercial simulation software and the source code is open to public, the model can be modified for use in a wide variety of process control research areas. For each unit, design assumptions, physical data, and modeling formulations are discussed. There are some differences between the TMODES model and the MATLAB model, and these differences together with the reasons for them are pointed out. Steady state values of the manipulated variables and major measurements in the base operation are given. Production objectives, process constraints, and process variability are summarized based on the earlier publication. All of the physical property, kinetic data, and process flowsheet information in the MATLAB model come from sources in the open literature.

The manufacturing process is about vapor-phase reaction converting ethylene (C_2H_4), oxygen (O_2) and acetic acid (HAc) into vinyl acetate (VAc) with water (H_2O) and carbon dioxide (CO_2) as byproducts. It has both gas and liquid recycle streams with real components. The process contain 10 basic unit operations that include a catalytic plug flow reactor, a feed-effluent heat exchanger (FEHE), a separator, a vaporizer, a gas compressor, an absorber, a carbon dioxide (CO_2) removal system, a gas removal system, a tank for the liquid recycle stream and an azeotropic distillation column with a decanter plants (Luyben and Tyrus, 1997). This process is focusing the data response of the column section to give the clear view of the controller performance. The control response of P, PI and Neural Network controller is observed for further analysis.

1.2 Problem Statement

Generally, the actual data of Vinyl Acetate Monomer (VAC) process is controlled by either P or PI control. The suitability using Neural Network Control alongside the actual P and PI control and the capability of the controller to improve the unsatisfied result is investigated and analyzed.

1.3 Objectives of Study

The aims of this study are:

To generate data the of control process in Vinyl Acetate Monomer (VAC) besides investigating the controller performance of PI and P control compared to Neural Network controllers in Vinyl Acetate Monomer (VAC) process.

1.4 Scope of Study

In order to achieve the objectives, the study is specified into those scopes:

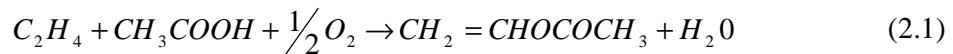
- a) To generate data from Vinyl Acetate (VAC) monomer process
- b) To simulate dynamic response of the data.
- c) To analyze the performance of the controller response of P, PI control and Neural Network control.
- d) To analyze and compare the performance of the controllers.

CHAPTER 2

LITERATURE REVIEW

2.1 The Vinyl Acetate Monomer (VAC) Process

The vinyl acetate monomer (VAC) manufacturing process consist 10 basic unit operation which include catalytic plug flow reactor, a feed-effluent heat exchanger (FEHE), a separator, a vaporizer, a gas compressor, an absorber, a carbon dioxide (CO₂) removal system, a gas removal system, a tank for the liquid recycle stream and an azeotropic distillation column with a decanter plants (Luyben and Tyrus, 1997). The manufacturing process is about vapor-phase reaction converting ethylene (C₂H₄), oxygen (O₂) and acetic acid (HAc) into vinyl acetate (VAc) with water (H₂O) and carbon dioxide (CO₂) as byproducts. An inert, ethane (C₂H₆), enters with the fresh ethylene feed stream. The reactions are as below:



The exothermic reactions occur in a reactor containing tubed packed with precious metal catalyst on a silica support. Heat is removed from the reactor by generating steam on the shell side of the tubes. Water flows to the reactor from a steam drum, to which make-up water (BFW) is provided. The steam leaves the drum as saturated vapor. The reactions are irreversible and the reaction rates have an Arrhenius-type dependence on temperature.

Figure 2.1 shows the process flow sheet with location of the manipulated variables. The numbers on the streams are the same as those given by Luyben and Tyreus (1997).

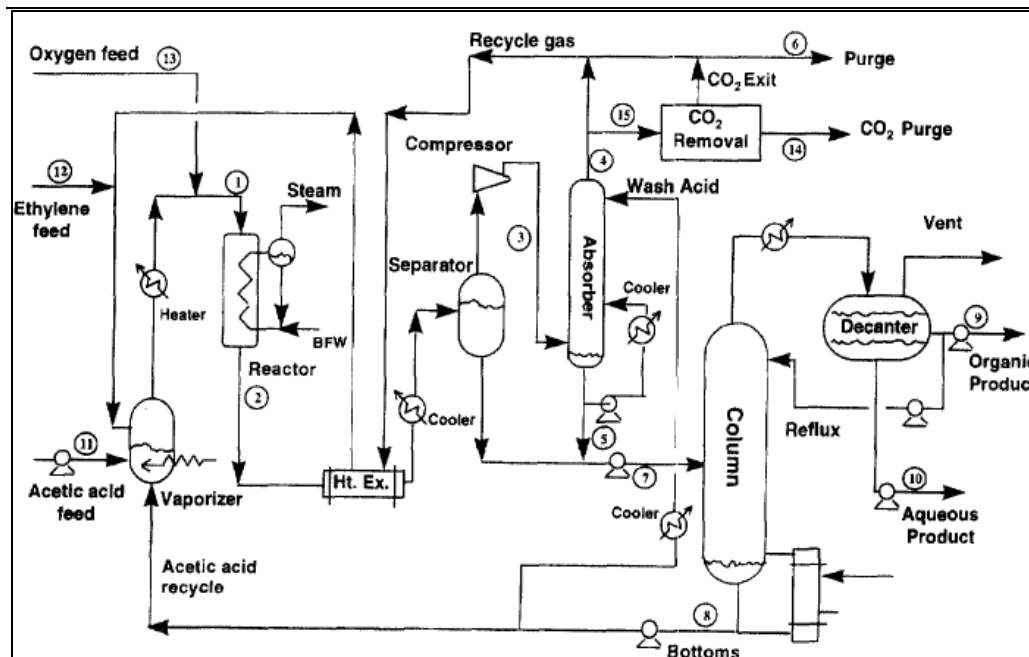


Figure 2.1: Vinyl acetate monomer process flowsheet

The reactor effluent leaves through a process-to-process heat exchanger, where the cold stream is the gas recycle. Then, the effluent is cooled with cooling water and the vapor (oxygen, ethylene, carbon dioxide and ethane) and liquid (vinyl acetate, water and acetic acid) are separated. The vapor stream from the separator goes to the compressor and the liquid stream from the separator becomes a part of the feed to the azeotropic distillation column. The gas from the compressor enters the bottom of an absorber, where the remaining vinyl acetate is recovered. A liquid stream from the base is recirculated by a cooler and fed to the middle of the absorber. To provide scrubbing, the liquid acetic acid that has been cooled is fed into the top of the absorber. The liquid bottoms product from the absorber combines with the liquid from the separator as the feed stream to the distillation column (Luyben and Tyreus, 1997).

Some of the overhead gas exiting the absorber enters the carbon dioxide removal system is simplified by treating it as component separator with a certain

efficiency that is a function of rate and composition. The gas stream minus carbon dioxide is split, with part going to the purge for removal of the inert ethane and the rest combines with large recycle gas stream goes to the feed-effluent heat exchanger also with added fresh ethylene feed stream. Steam is used to vaporize the liquid in the vaporizer where the gas recycle stream, the fresh acetic acid feed and the recycle liquid acetic acid enters. The gas stream from the vaporizer is further heated to the desired reactor inlet temperature in a trim heater using steam. To keep the oxygen composition in the recycle loop outside the explosives region, fresh oxygen is added to the gas stream from the vaporizer.

The azeotropic distillation column then separates the vinyl acetate and water from the unconverted acetic acid. The overhead product is condensed with cooling water and the liquid goes to the decanter, where the vinyl acetate and water phase separate. The bottom product from the distillation column contains acetic acid, which recycles back to the vaporizer along with fresh make-up acetic acid. Part of this bottom product is the wash acid used in the absorber after being cooled (Mc Avoy, 1998).

2.2 Feedback Control

In general process, feedback control process has an output y , a potential disturbance d , and an available manipulated variable m . (George Stephanopoulos, 2004). The process is shown in Figure 2.2 below:

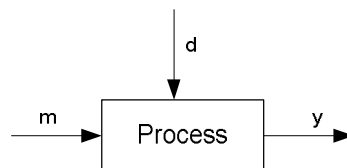


Figure 2.2: General process block diagram

The disturbances, d or load change is an unpredictable manner and the aim of the control process is to keep the value of the output, y at the desired levels. A feedback control action takes the following steps. First, the value of the output (flow,

pressure, liquid level, temperature, composition) will be determined using the appropriate measuring device with y_m be the value indicated by the measuring sensor. Then, the indicated value y_m is compared to the desired value y_{sp} (set point) of the output and the deviation (error) would be $e = y_{sp} - y_m$. The value of the deviation e is supplied to the main controller. The controller in turn changes the value of the manipulated variable m in such way as to reduce the magnitude of the deviation e . Usually the controller does not affect the manipulated variable directly but through another device (usually a control valve), known as the final control element.

Figure 2.3 shows the notified steps. The system in Figure 2.2 is known as open loop, in contrast to the feedback controlled system in Figure 2.3 which is called closed loop. When value of d or m change, the response of the first step is categorized open loop response while the second step is the closed loop response.

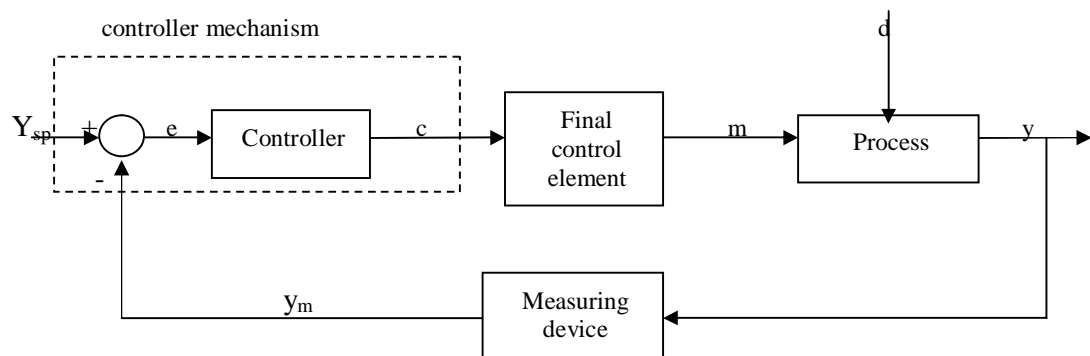


Figure 2.3: Corresponding feedback loop

2.3 Block Diagram and the Closed-Loop Response

For the generalized closed-loop system showed in Figure 2.4, it has four components (process, measuring device, controller mechanism and final control element) which corresponding transfer functions relating its output to the inputs can be written.

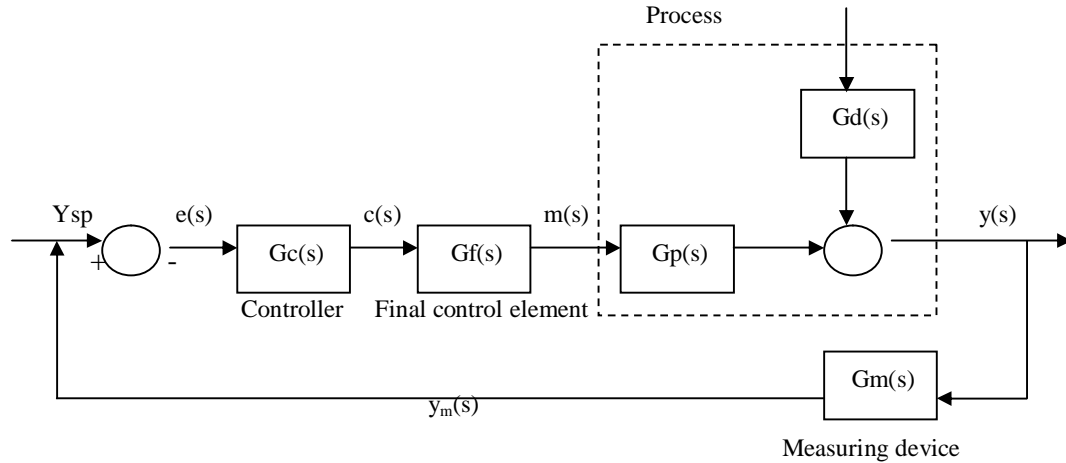


Figure 2.4: The generalized close-loop system

In particular, if the dynamics of the transmission lines, are neglect:

Process:

$$\bar{y}(s) = G_p(s)\bar{m}(s) + G_d(s)\bar{d}(s) \quad (2.3)$$

Measuring device:

$$\bar{y}_m(s) = G_m(s)\bar{y}(s) \quad (2.4)$$

Controller mechanism:

$$\bar{\epsilon}(s) = \bar{y}_{sp}(s) - \bar{y}_m(s) \text{ comparator} \quad (2.5)$$

$$\bar{c}(s) = G_c(s)\bar{\epsilon}(s) \text{ control action} \quad (2.6)$$

Final Control Element :

$$\bar{m}(s) = G_f(s)\bar{c}(s) \quad (2.7)$$

where G_p , G_d , G_m , G_c and G_f are the transfer function between the corresponding inputs and outputs (McMillan, 1994). The series of blocks between the comparator and the controlled output (i.e., G_c , G_f and G_p) constitutes the forward path, while

the block G_m is on the feedback path between the controlled output and the comparator.

Algebraic manipulation of the equations above yields

$$\bar{m}(s) = G_f(s)G_c(s)[\bar{y}_{SP}(s) - G_m(s)\bar{y}(s)] \quad (2.8)$$

completing back the equation (2.3) give:

$$\bar{y}(s) = G_p(s)\{G_f(s)G_c(s)[\bar{y}_{SP}(s) - G_m(s)\bar{y}(s)]\} + G_d(s)\bar{d}(s) \quad (2.9)$$

and after readjusting

$$\bar{y}(s) = \frac{G_p(s)G_f(s)G_c(s)}{1 + G_p(s)G_f(s)G_c(s)G_m(s)}\bar{y}_{SP}(s) + \frac{G_d(s)}{1 + G_p(s)G_f(s)G_c(s)G_m(s)}\bar{d}(s) \quad (2.10)$$

This equation gives the closed-loop response of the process. It is composed of two terms. The first term shows the effect on the output of change in the set point, while the second term tells the effect on the output of a change in the load (disturbance). The corresponding transfer functions are known as closed-loop transfer functions. In particular,

$$\frac{G_p}{1 + GG_m} = G_{SP} \quad (2.11)$$

is the closed loop transfer function for a change in the set point and

$$\frac{G_d}{1 + GG_m} = G_{load} \quad (2.12)$$

is the closed loop transfer function for a change in the load.

2.4 Proportional Integral Derivate (PID) Controller

There are some type of controllers that can be used in the control system in order to get the observation of the step change in set point (set point tracking) and the step change in load (disturbance rejection). Among the type of controllers are proportional (P) control, proportional-integral (PI) control and proportional-integral-derivatives (PID) control.

2.4.1 Effect on Proportional (P) Control

As known, the closed-loop response of a process is given by equation (2.10). To ease the analysis assumption is made that:

$$G_m(s) = 1, \quad G_f(s) = 1 \quad \text{and} \quad G_c(s) = K_c \text{ (proportional controller)}$$

then the equation become

$$\bar{y}(s) = \frac{G_p(s)K_c}{1 + G_p(s)K_c} y_{SP} + \frac{G_d(s)}{1 + G_p(s)K_c} \bar{d}(s) \quad (2.13)$$

for first order systems yield

$$\bar{y}(s) = \frac{K_p}{t_p s + 1} \bar{m}(s) + \frac{K_d}{t_p s + 1} \bar{d}(s) \quad (2.14)$$

Then, for uncontrolled system, where

$$G_p(s) = \frac{K_p}{t_p s + 1} \quad \text{and} \quad G_d(s) = \frac{K_d}{t_p s + 1}$$

included in equation (2.13) and yield the closed-loop response:

$$\bar{y}(s) = \frac{K_p K_c}{t_p s + 1 + K_p K_c} \bar{y}_{SP}(s) + \frac{K_d}{t_p s + 1 + K_p K_c} \bar{d}(s) \quad (2.15)$$

readjust

$$\bar{y}(s) = \frac{K'_p}{t'_ps + 1} \bar{y}_{sp}(s) + \frac{K'_d}{t'_ps + 1} \bar{d}(s) \quad (2.16)$$

where

$$t'_p = \frac{t_p}{1 + K_p K_c}, \quad K'_p = \frac{K_p K_c}{1 + K_p K_c} \quad \text{and} \quad K'_d = \frac{K_d}{1 + K_p K_c}$$

K'_p and K'_d also known closed-loop static gains.

As the result the closed-loop response of a first order system is still is the first order system with respect to load and set point changes. The closed-loop response has become faster than the open-loop response to the change in set point or load, due to the time constant that has been reduced and also the static gains that have been decreased.

In order to get better observation to the effect of this proportional controller, the resulting closed-loop responses is reviewed and examined with set point and the disturbance changes.

For change in the set point where $\bar{y}_{sp} = \frac{1}{s}$ and $\bar{d}(s) = 0$, which insert to equation (2.16) resulting

$$\bar{y}(s) = \frac{K'_p}{t'_ps + 1} \frac{1}{s}$$

in the inverse mode give

$$y(t) = K'_p (1 - e^{-t/t'_p}) \quad (2.17)$$

Figure 2.5 view the response of the closed loop response to set point change. The ultimate response, after $t \rightarrow \infty$, never reaches the desired new set point. There is a discrepancy called offset which is equal to

$$\begin{aligned} \text{offset} &= (\text{new set point}) - (\text{ultimate value of the response}) \\ &= 1 - K'_p \\ &= \frac{1}{1 + K_p K_c} \end{aligned}$$

The offset is the effect of proportional control. It decreases as K_c becomes larger and generally

offset $\rightarrow 0$ when $K_c \rightarrow \infty$

For change in the disturbance, $\bar{y}_{sp}(s) = 0$ and $\bar{d}(s) = \frac{1}{s}$. Hence the equation (2.17)

become

$$\bar{y}(s) = \frac{K'_d}{t'_p} \frac{1}{s+1}$$

inverse give

$$y(t) = K'_d (1 - e^{-t/t'_p}) \quad (2.18)$$

Response in the disturbance change is shown in Figure 2.6. Again the proportional controller cannot keep the response at the desired set point but it exhibits an offset:

$$\begin{aligned} \text{offset} &= (\text{set point}) - (\text{ultimate value of response}) \\ &= 0 - K'_d \\ &= -\frac{K_d}{1 + K_p K_c} \end{aligned}$$

The advantage of the proportional control in the presence of disturbance changes, the response is much closer to the desired set point than not have control at all (Lee, 1998). This effect can be viewed from the Figure 2.6. If the gain K_c is increased the offset decreases and theoretically

offset $\rightarrow 0$ when $K_c \rightarrow \infty$

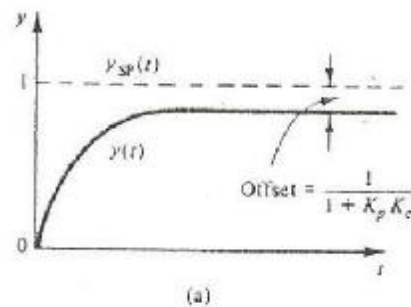


Figure 2.5: Closed-loop response of set point change

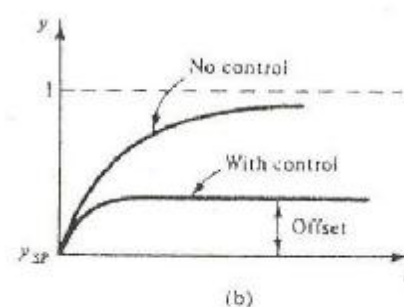


Figure 2.6: Closed-loop response of disturbance change

2.4.2 Effect on Proportional Integral (PI) control

Instead using proportional control alone, it is almost never the case for integral or derivative control actions. Hence, proportional integral (PI) and proportional-integral-derivative (PID) are the common controllers employing integral and derivative modes of control. (Seborg, 2004).

Combination of proportional and integral control leads to the effect on response of a closed-loop system such as the increase of order of the response and the eliminated of offset (effect of integral mode). It also yield faster response as K_c increases, (effect of proportional and integral modes), more oscillation to set point changes such as the overshoot and decay ratio increase (effect of integral mode). Also large value of K_c creates a very sensitive response and may lead to instability. Yet, when τ_1 decrease for constant K_c , the response become faster but more oscillatory with higher overshoots and decay ratios (effect of integral mode).

2.4.3 Effect on Proportional Integral Derivative (PID) control

As stated before, the presence of the integral control will slows down the closed-loop response. Then, to speed up the closed-loop response the value of the controller gain K_c may need increasing but in acceptable speeds in order to avoid instability response that become more oscillatory. Stabilizing effect can be achieved to the system by introduce the derivative mode. Then acceptable response speed can be hold by choosing the suitable value for the gain K_c while maintaining moderate overshoots and decay ratios.

Figure 2.7 below shows the effect of PID controller on the response of the controlled process. Note that although increasing K_c leads to faster responses, the overshoot remains almost the same and the settling time is shorter. Both are the results of the derivative control action.

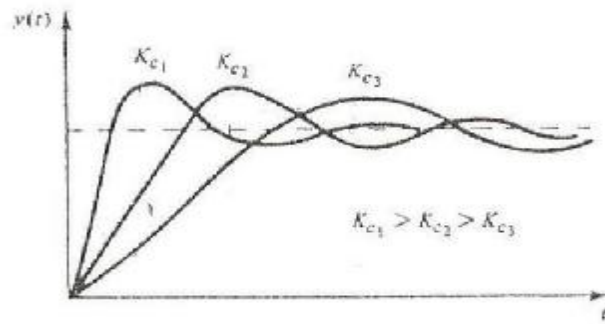


Figure 2.7: Effect of gain on the closed-loop response with PID control

2.5 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) basically is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons or nodes that process information using a connectionist approach to computation. Neural Network is one of solution for modeling problems. Among advantages of neural network as described by Baughman and Liu (1995) are:

- a) *Learning ability of ANN* that able to adjust its parameters in order to adapt itself to changes in the surrounding systems by using an error-correction training algorithm.
- b) *Imitation of the human learning process* of the network that can be trained iteratively, and by tuning the strengths of the parameters based on observed results. The network can develop its own knowledge base and determine cause and effect relations after repeated training and adjustments.
- c) *On-line use capability* of ANN that can yield results from a given input relatively quickly once trained,, which is a desired feature for the on-line use.

As the network consist of group of nodes, Figure 2.8 shows single processing node of the network receives one or more input signals, u_i , which may come from other nodes or from some other source. Each input is weighted according to the value $w_{i,j}$ that is called *weight*. These weights are similar to the synaptic strength between two connected neurons in the human brain. The weighted signals to the node are summed and the resulting signal, called the *activation*, h , is sent to the *transfer function*, g , which can be any type of mathematical function, but is usually taken to be a simple bounded differentiable function such as the sigmoid. The resulting output of the node y_i , may then be sent to one or more nodes as an input or taken as the output of a NN model.

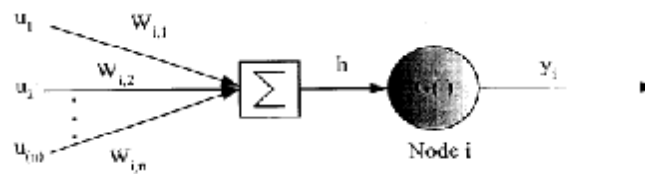


Figure 2.8: Single processing node.

Figure 2.9 then shows network that consist of nodes that is interconnected arranged into several layers. Group of nodes called input layer receive signal from external source. This input layer does not process signal unless needs scaling. The output layer returns the signals to the external environment and the hidden layer is layer that consists of hidden nodes that do not receive any signals from or to external source. Each of the connection between the nodes has the associated weight respectively.

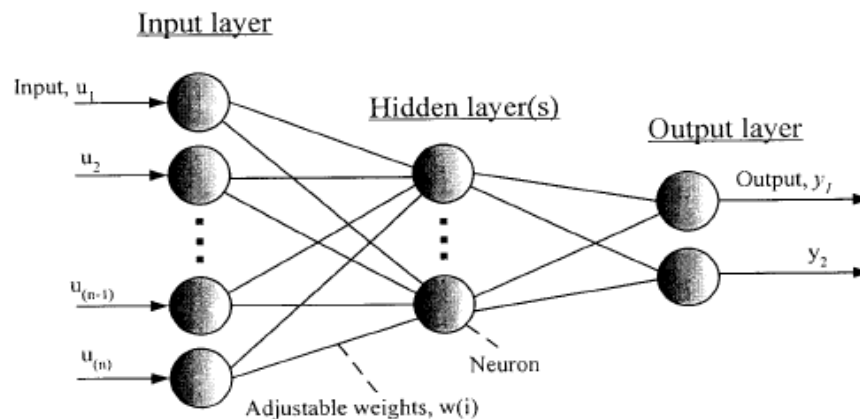


Figure 2.9: Neural Network Layer

Due to the complexity of the network, analytical method of calculating the values of the weights for a particular network to represent process behaviour is not discouraging. Instead the network must be *trained* on a set of data (called the *training* collected from the process to be modelled. Training is a procedure of estimating the values of the weights and establishing the network structure, and the algorithm used to this is called a “learning” algorithm. The learning algorithm is essentially an optimization algorithm. Once a network is trained, it can be conveniently used as a model to represent the system for various different purposes.

CHAPTER 3

METHODOLOGY

3.1 Overview

Initially, the collection and generation of the data of Vinyl Acetate (VAC) process is done and the dynamic response of the process data is run to observe the pattern. Then, the study is focusing on data from column section process to minimize the data to be controlled and observed. The implementation of the function in the P, PI control and Neural Network control is done in MATLAB environment. After getting the result of control process of P and PI control, the Neural Network Control is implemented to the unsatisfied result of P and PI control to see changes. At the end the comparison and analysis of the performance between the PID control and Neural Network control is investigated discussed.

3.2 Work Flow

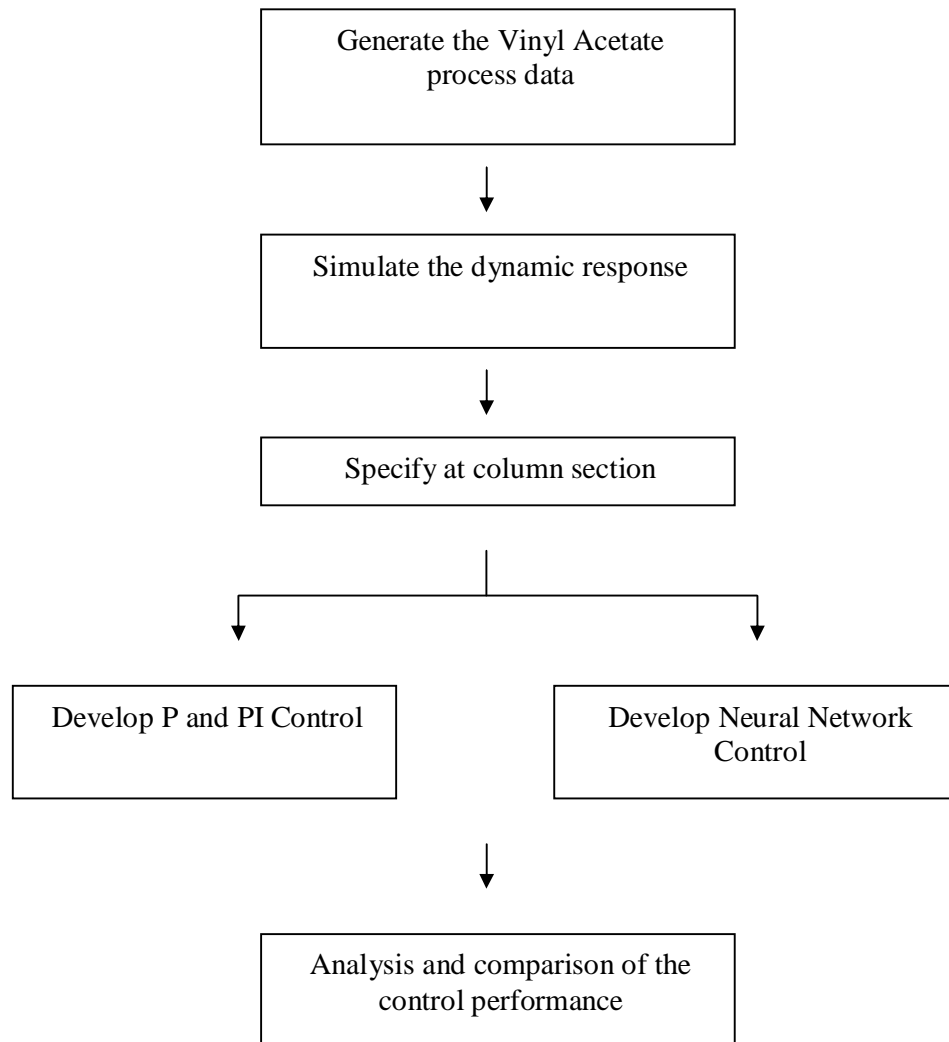


Figure 3.1: Work flow diagram

3.3 Data Generation

The M-file in Figure 3.2 contains generation of data by function of `test_VAcPlant(t, ID)` where `t` is the simulation time (in minute) and `ID` is an integer selected between 0 and 8. There are eight process disturbances are available and transients are generated at the end of simulation to get the result. All the disturbances occur at 10 minute after the simulation starts where function of 0 for no disturbance, 1 for setpoint of the reactor outlet temperature decreases 8 °C (from 159 to 151), 2 for setpoint of the reactor outlet temperature increases 6 °C (from 159 to 165) and 3 for setpoint of the H₂O composition in the column bottom increases 9% (from 9% to 18%). Next, ID of 4 is for the vaporizer liquid inlet flowrate increases 0.44 kmol/min (from 2.2 to 2.64), 5 for HAc fresh feed stream lost for 5 minutes and 6 for O₂ fresh feed stream lost for 5 minutes. Lastly, ID of 7 is stands for C₂H₆ composition changes from 0.001 to 0.003 in the C₂H₄ fresh feed stream and ID of 8 is for column feed lost for 5 minutes.

```

1  test_VAcPlant.m: ID is an integer, which means you can use the function to simulate
2  (In this example, Logixes a multi-loop control structure is implemented and tested
3  (Eight process disturbances are available and transients are generated at the end of simulation
4  (On a FIJI-100s PC, the VAc plant model runs approximately 60 times faster than the real time
5  (To use this example:
6  (1) Set the time axis time (in minutes)
7  (2) ID is an integer selected between 0 and 8:
8  (3) 0: no disturbance
9  (4) 1: setpoint of the reactor outlet temperature decreases 8 degC (from 159 to 151)
10 (5) 2: setpoint of the reactor outlet temperature increases 6 degC (from 159 to 165)
11 (6) 3: setpoint of the H2O composition in the column bottom increases 9% (from 9% to 18%)
12 (7) 4: the vaporizer liquid inlet flowrate increases 0.44 kmol/min (from 2.2 to 2.64)
13 (8) 5: HAc fresh feed stream lost for 5 minutes
14 (9) 6: O2 fresh feed stream lost for 5 minutes
15 (10) 7: C2H6 composition changes from 0.001 to 0.003 in the C2H4 fresh feed stream
16 (11) 8: column feed lost for 5 minutes
17 (Note: In this example, all the disturbances occur at 10 minutes after the simulation starts
18
19 -----
20 Copyright: Feiqi Chen and Eshel David, June 2002
21
22 function test_VAcPlant(t, ID)
23
24 -----
25 close all
26 format short g
27
28 -----
29
30 (The recommended simulation sampling time is 1/3 second, which corresponds to a frequency of 300 samples in one minute
31 model_comp_inp.frequency=180;
32 (The recommended historical data position time is 1 minute, which corresponds to a frequency of 1 sample in one minute
33 average_avg_inp.frequency=1;
34 (The recommended display sampling time is 1 minute, which corresponds to a frequency of 1 sample in one minute
35 display_avg_inp.frequency=1;
36
37
38
39

```

Figure 3.2: Data Generation

3.4 Specifying Column Section

As being shown in Figure 3.3, the focus is at the column section where it is MV24 in the M-file data. Since specified at the column section, the change is only made in this section. Among transmitter and controller initialization is SP for setpoint, K for controller gain which is dimensionless and Ti for reset time (in minute). Next is act of 1 if positive process gain, -1 if negative process gain and mode of 1 for automatic, 2 for manual. The result of the specification at column data will yield result of six data that being controlled that is percentage of water in the column bottom (%H₂O), column temperature (Col-T), decanter organic level (Org-L), decanter aqueous level (Aqua-L), column bottom level (Col-L) and vapor flowrate at top column (Vap-In).

```

655 - end
656 - for i=1:Ntau_Aqueous
657 -     yyy_Aqueous(i) = xxx_Aqueous(Ntau_Aqueous);
658 - end
659 - xl_Aqueous = (MVs(24) - uLO_ColButton) / (uHI_Aqueous - uLO_Aqueous * E_Aqueous * act_ColButton * (SP_Aqueous - yLO_Aqueous)) / yHI
660 -
661 - %MV24: Column Bottom Exit is used to control the Column Bottom Level.
662 - SP_ColButton=0.5;
663 - K_ColButton=1;
664 - Ti_ColButton=0;
665 - act_ColButton=-1;
666 - mode_ColButton=1;
667 - Ponig_ColButton=1;
668 - hc_ColButton=1/transmitter_sampling_frequency(25);
669 - hc_ColButton=1/controller_sampling_frequency(25);
670 - uLO_ColButton=0;
671 - uHI_ColButton=4.536;
672 - ded_ColButton=transmitter_deadtime(25);
673 - tau_ColButton=transmitter_lag;
674 - yLO_ColButton=0;
675 - yHI_ColButton=1;
676 - EMed_ColButton=1/transmitter_deadtime(25)*transmitter_sampling_frequency(25);
677 - Ntau_ColButton=1;
678 - xxx_ColButton(i) = (y_pp(21)-yLO_ColButton) / (yHI_ColButton - yLO_ColButton);
679 - for i=0:Nded_ColButton
680 -     xxx_ColButton(i) = xxx_ColButton(1);
681 - end
682 - for i=1:Ntau_ColButton
683 -     yyy_ColButton(i) = xxx_ColButton(Nded_ColButton);
684 - end
685 - xl_ColButton = (MVs(25) - uLO_ColButton) / (uHI_ColButton - uLO_ColButton * X_ColButton * act_ColButton * (SP_ColButton - yLO_
686 -
687 - %controller initialization

```

Figure 3.3: Column section

3.5 Proportional (P) and Proportional Integral (PI) Control

The data of the process is being tested and controlled in either P or PI control only because the process data not have the PID control implementation and we only tested the result of P and PI control. The function for the controller setting is Ponly of 1 for proportional control, and 0 for PI control as shown in Figure 3.3. Although result of P and PI control with disturbance can be run by function of ID equal to 8 that is column feed lost for 5 minutes, the result that considered for improvement is the one with no disturbance present.

3.6 Neural Network Control

After getting the result from P and PI control, two results that show some unsatisfying condition is selected to be implemented in Neural Network control to see the changes. The comparison of the controller then is more reliable when focusing to the two results (Su and McAvoy, 1997). After implementation of Neural Network control, the improved result is run again to the process to see the final result. Among the steps taken in implemented or trained the data are:

- a) two unsatisfied data result of the P and PI control is taken to be controlled by Neural Network.
- b) both data is prepared, scaled, and trained in Matlab environment as shown in Figure 3.4.
- c) the improved data is run again in the process to see the differences.

```

1 - clear
2 - [input,output,validp,valido,sj]*=load('data.mat');
3 - ptr=input; ttr=output; %training variable
4 - v.P=input; v.T=valido; %validation variable
5 - hd=25; %number of hidden nodes
6
7 %creating a feedforward network
8
9 net=newff(input,[hd 1],{'logsig','purelin'},'trainlm');
10 net.trainparam.epochs=500;
11 net.trainparam.goal=1e-6;
12 net.trainparam.max_fail=15;
13 net.trainparam.show=50;
14 net=init(net);
15
16 h=waitbar(0,'Training and validation are in progress...');
17 for i=1:450,
18     waitbar(i/500,h);
19 end
20
21 %validating the net
22
23 [net,tr]=train(net,ptr,etc,[] ,[],v);
24
25 % plot fitnet
26
27 %calculate the error
28
29 load('data.mat');
30 [a,b]=size(y_history);
31 ans=size(net,input);
32
33
34 %evaluate=[sum(abs(y_history(:,b))-ans(y_history(:,b)))];

```

Figure 3.4: Neural Network implementation and training

CHAPTER 4

RESULT AND DISCUSSION

4.1 Overview

After the data is well-generate, the dynamic response of the data is generally done to see the overall results that contain all the data result from each unit operation. Then, focus at column section data is done and the data is being controlled with P and PI control. The results contain six response data of the column section process. Next, the unsatisfied result of P and PI control that is decanter organic level (Org-L) and vapor flowrate (Vap-In) is taken to develop and trained in Neural Network for further observations. Finally the trained data of Neural Network control is run back to the process to see improvement. The analysis is done then and positive result of Neural Network control is achieved.

4.2 Results for P Control

Generally, P controller is usually used for level control and others like temperature and pressure is usually controlled by PI or PID controller (Shinsky, 1996). In this process, to develop the result of P control, the setting is made in the transfer function of data file to activate the P controller and yield the result in Figure 4.1. The percentage of H₂O stands for controlled variable percent water in the column bottom and manipulated variable of column reflux flow rate set point (Luyben and Tyrus, 1997). As been showed, the result is falls near to the set point value at 9.344% although it's not good in the early minute. Same also goes to column temperature, decanter aqueous level and column bottom level that not really have good reading at the beginning but followed the set point at the end of the process. The only problem is at the result at organic level and vapor inlet that not even near to the set point.

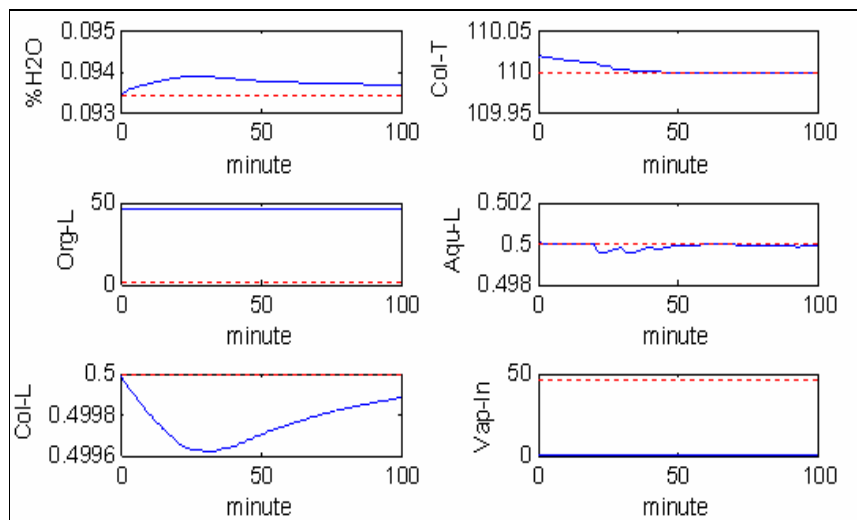


Figure 4.1: Results for P controller

4.3 Results for PI control

For PI controller, the result is relatively in similar condition to the PI controller. The only difference is the activation of t value in the transfer function compared to P control that is no present of t value (Astrom and Hagglund, 1995). This situation tells that the controller setting of P or PI not really effect or change the result of the simulation process. The controller is rather done their job enough to control the process or the process not really effect by the difference control setting of P or PI controller. Also noted in Figure 4.2 below, the data of Org-L and Vap-In is in not satisfying condition and need to be improved.

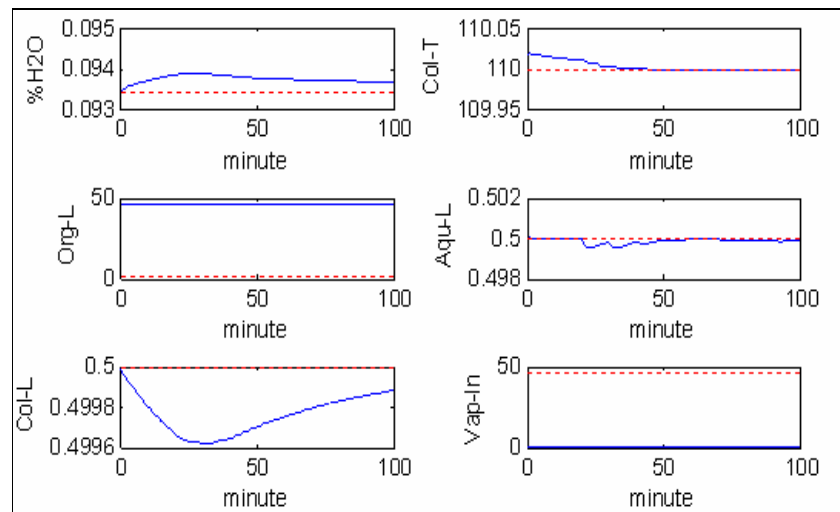


Figure 4.2: Results for PI controller

4.4 Disturbance Present of P control

The result with the disturbance present of P control is done by develop the ID value at the transfer function of file data. The disturbance setting of the process at the column section is ID value of 8 that stands for column feed lost for 5 minutes. As showed in Figure 4.3, the process are being disturbed at approximate minutes of 10 (where every disturbance is applied after 10 minute run) and stabilize after minute of 50. It's shows the controller reacts quite fast to deal with the problems and the reading is stabilized at the end of the minute. The result shows the capability of P control against the disturbance. However the result that being considered to be improved is the results without the disturbance present.

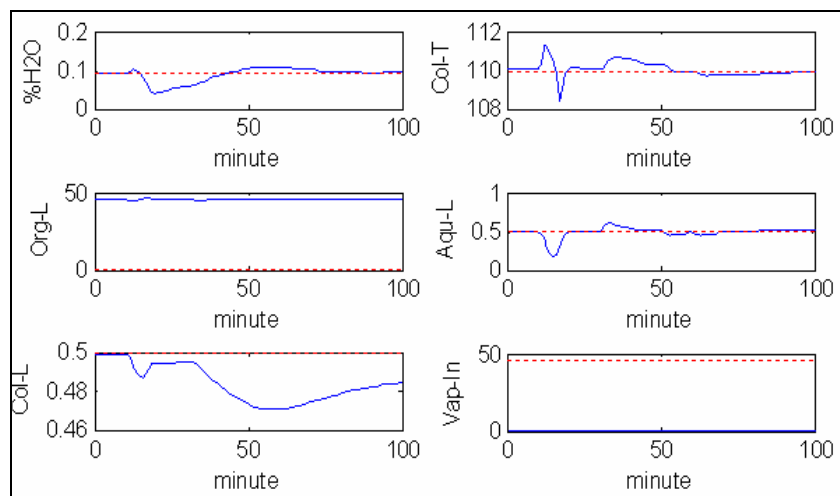


Figure 4.3: Results for P controller with disturbance

4.5 Disturbance Present of PI control

The result with the disturbance present of PI control is done by similar step that is develop the ID value of 8 at the transfer function of file data that stands for column feed lost for 5 minutes. As showed in Figure 4.4, the process is being disturbed at approximate minutes of 10 (where every disturbance is applied after 10 minute run) and stabilized after minute of 50. Its shows the controller capability similar to P control that reacts quite fast to deal with the problems and the reading is stabilized at the end of the minute. Although the result shows such capability of control against the disturbance, the result that being considered to be improved is only the result without the disturbance present.

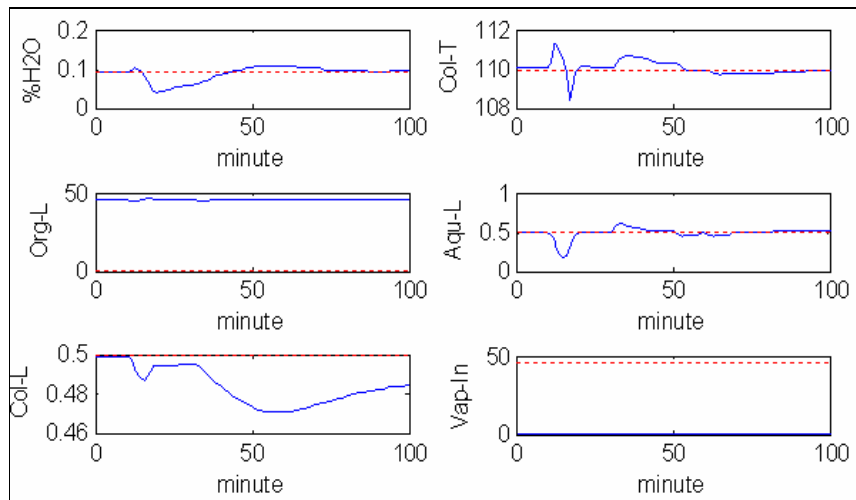


Figure 4.4: Results for PI controller with disturbance

4.6 The Identified Data

In order to develop Neural Network control, two data result of P and PI control is decided to be taken to further development. As shown in Figure 4.5, the response data of the Vap-In process is taken according its unsatisfied control behavior. The view of difference reading of response and the actual setpoint is clearly observed. The response of the process is in range 44 to 45 kmol/hr while the actual setpoint is around 0 to 1 kmol/hr. This data of process then is prepared to be implemented in Neural Network control to see changes.

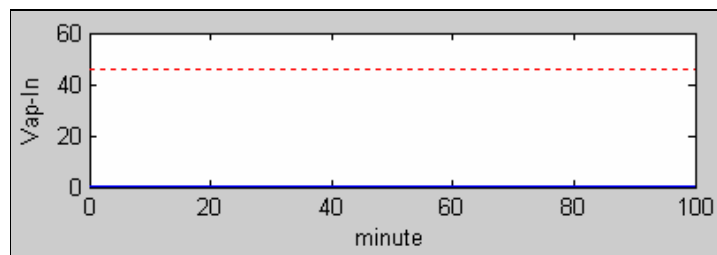


Figure 4.5: Vapor-In Response of P and PI control

Similar to the result of Vapor-In, the response result of P and PI control of organic level in decanter is taken to be further development as the reading of the response are so far from the actual setpoint. As shown in Figure 4.6, the actual setpoint is around 0 to 1 mol percentage while the response is around 44 to 45 mol percentage. This data of process is also prepared to be implement in Neural Network Control to observe changes.

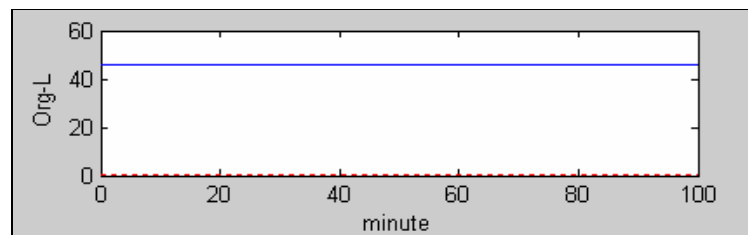


Figure 4.6: Organic Level Response of P and PI control

4.7 Training and Validation

In order to develop the identified data in Neural Network control, the data must be prepared, scaled and trained with no of hidden nodes in the network (Haykin, 1999). The data has trained with various no of hidden nodes that is 1 up to 25 nodes. Each result has the value of the mean square errors for the training and validations that refers to the network strength of the control process. The smallest mean square errors, the better the network (Psychogios and Ungar, 1991). The results of mean square error value of Vapor In (Vap-In) as shown in Table 4.1. Figure 4.7 shows the best training and validation behavior of the Vapor In (Vap-In) data according to the selection of best training behavior and smallest combination of mean square error.

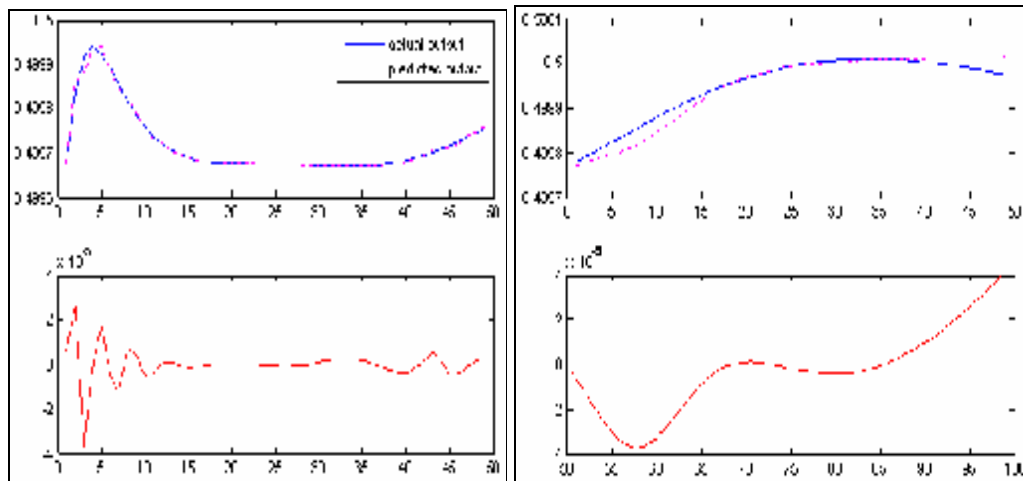


Figure 4.7: Training and Validation for Vapor In (Vap-In)

Hidden nodes	Trainmse	Valmse
1	2.21E-08	1.33E-08
2	1.03E-09	2.66E-09
3	7.92E-10	1.52E-09
4	1.38E-09	1.06E-08
5	5.09E-08	3.25E-09
6	3.17E-08	7.41E-09
7	1.03E-09	3.39E-08
8	1.00E-09	4.26E-09
9	2.45E-09	4.91E-08
10	2.59E-07	1.91E-08
11	1.75E-07	7.02E-08
12	1.98E-09	1.67E-10

13	1.05E-09	5.40E-08
14	1.23E-07	1.07E-08
15	1.31E-08	2.33E-08
16	1.25E-07	6.53E-08
17	6.90E-08	5.16E-09
18	1.43E-07	2.21E-08
19	5.65E-08	7.09E-08
20	3.65E-10	6.11E-09
21	1.53E-08	1.38E-08
22	7.77E-08	3.60E-08
23	8.96E-08	2.64E-08
24	1.77E-08	6.30E-10
25	5.07E-10	1.32E-08

Table 4.1: Mean square error for validation and training of Vapor In (Vap-In)

As shown in Figure 4.8, the step for getting the result of training and validation for the Neural Network control is same for Organic Level (Org-L) data. The data has prepared, scaled and trained with no of hidden nodes in the network. The data also has trained with various no of hidden nodes that is 1 up to 25 nodes. Each result has the value of the mean square errors for the training and validations that refers to the network strength of the control process. The smallest mean square errors, the better the network. The results of mean square error value for Organic Level (Org-L) as shown in Table 4.2.

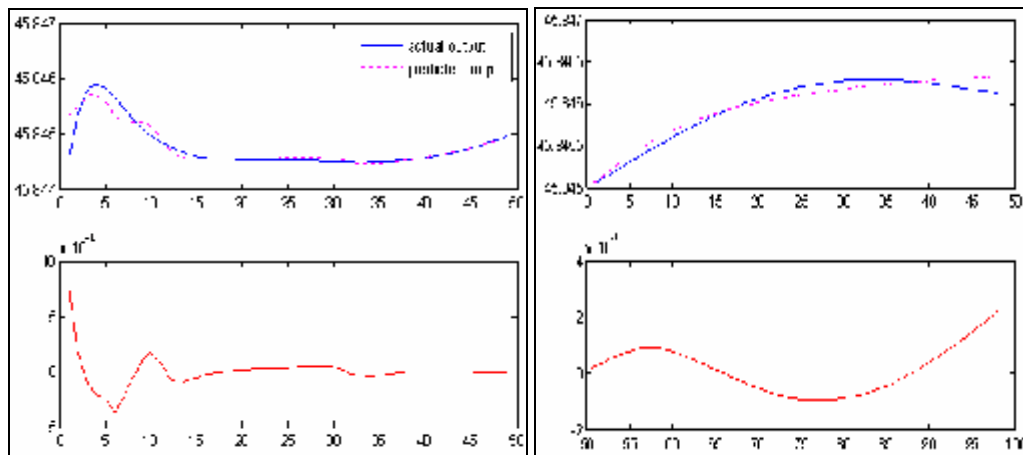


Figure 4.8: Training and Validation for Organic Level (Org-L)

Hidden notes	Trainmse	Valmse
1	3.31E-08	3.05E-07
2	5.07E-07	8.26E-08
3	2.01E-08	2.48E-08
4	2.15E-08	7.51E-09
5	3.09E-08	5.17E-07
6	1.49E-08	1.27E-06
7	2.13E-08	1.63E-07
8	8.79E-07	4.76E-07
9	4.39E-06	2.06E-06
10	5.29E-07	4.07E-07
11	8.19E-09	2.78E-07
12	4.32E-09	1.82E-07
13	1.10E-07	7.49E-08
14	7.12E-07	1.93E-07
15	3.62E-08	3.55E-08
16	6.95E-07	9.39E-07
17	8.14E-07	4.91E-09
18	2.27E-06	2.26E-07
19	3.23E-06	3.66E-07
20	4.25E-08	2.08E-06
21	5.44E-08	1.68E-06
22	4.44E-07	6.21E-08
23	3.81E-06	5.73E-07
24	1.22E-07	1.23E-07
25	4.52E-07	1.41E-08

Table 4.2: Mean square error for validation and training of Organic Level (Org-L)

4.8 Final Result of Neural Network Control

After the data of the Neural Network has been trained, the improved result is run again to the process to observe the changes. The results of the final control process of the Neural Network are shown in Figure 4.9 and Figure 4.10 below. As shown in Figure 4.9, the response of the processing data is well-improved and relatively relevant to the actual setpoint. The same scenario also is seen in final result of Neural Network control for Organic Level processing data as shown in Figure 4.10 although it is not really satisfying in the beginning of the process. The possibility of error correction of the response processing data is shown in this situation.

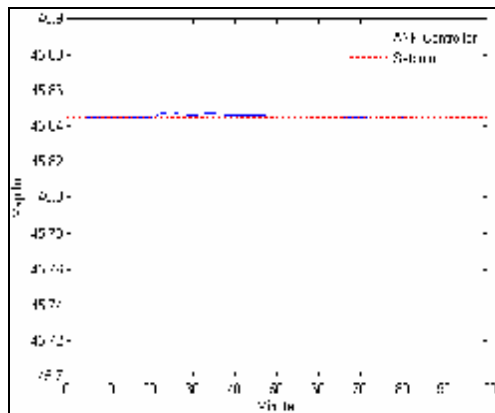


Figure 4.9: Final Result of Neural Network Control for Vapor In (Vap-In)

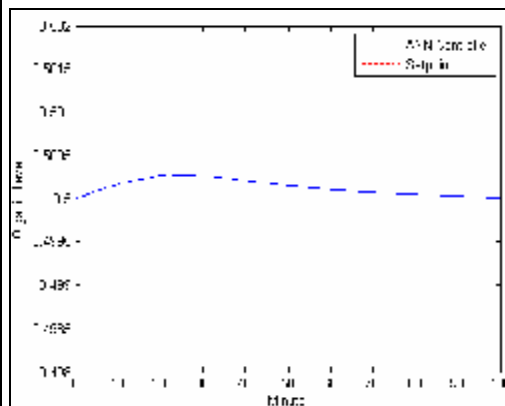


Figure 4.10: Final Result of Neural Network Control for Organic Level (Org-L)

4.9 Comparison and Analysis

As the result, the comparison of the controller performance can be observed and discussed. As shown in Figure 4.11 and Figure 4.12 the improvement of the control process can be clearly seen. The data process response of the early P and PI control is far over the actual setpoint value that is at 45.845 kmol/hr. After the processing data has been implemented in Neural Network control and rerun back to the process, the response of the process data has improved and more relevant to the actual setpoint. This shows the capability of the Neural Network to improve the error of the response data.

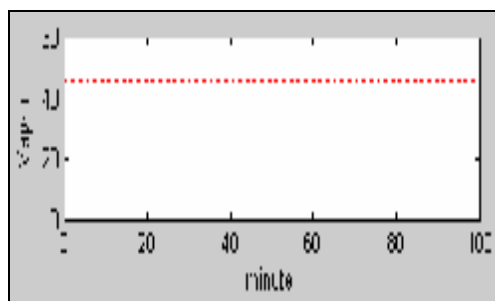


Figure 4.11: Result of P and PI control for Vapor In (Vap-In)

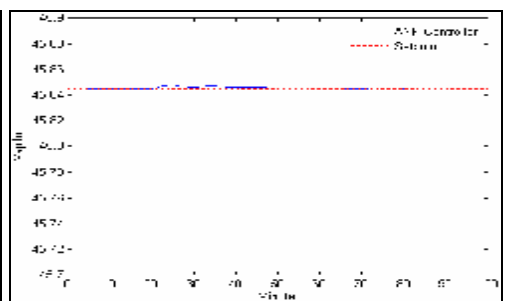


Figure 4.12: Final Result of Neural Network Control for Vapor In (Vap-In)

The similar comparison of the controller performance can be seen and discussed for processing data of Organic Level (Org-L). As shown in Figure 4.13 and Figure 4.14 the improvement of the control process can be clearly observed. The data process response of the early P and PI control is far over the actual setpoint value that is at 0.5 percentage mole. After the processing data has been implemented in Neural Network control and rerun back to the process, the response of the process data has improved and more reliable to the actual setpoint. This shows the potential of the Neural Network to improve the error of the response data.

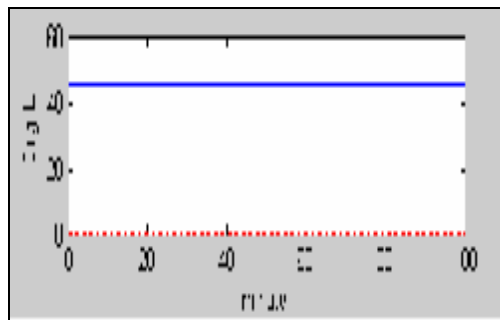


Figure 4.13: Result of P and PI control for Organic Level (Org-L)

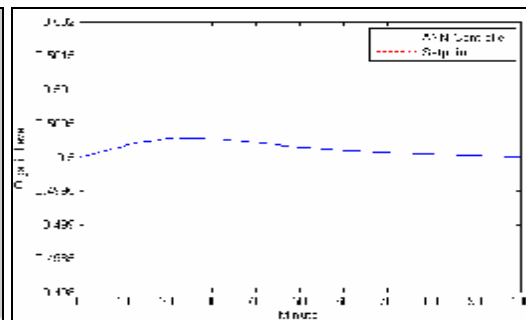


Figure 4.14: Final Result of Neural Network Control for Organic Level (Org-L)

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

As the result and discussions have been discussed, the objective and the overall process of the study are being reviewed. The target of the study as stated are to generate data the of control process in Vinyl Acetate Monomer (VAC) besides investigating the controller performance of PI and P control compared to Neural Network controllers in Vinyl Acetate Monomer (VAC) process.

The literature review of the study have been done and stated in order to get clear and concrete understanding about the details of the process and the control system. Method of the study is been followed then in order to ensure that the research is done with proper way. Next, the generation data of the process is successfully done in order to get the dynamic response of the data. The focus of the data is on the column section to get the better view of the control process.

The results of the control process of P and PI control at the column section has been collected and yield six response of data that is percentage of water in the column bottom (%H₂O), column temperature (Col-T), decanter organic level (Org-L), decanter aqueous level (Aqua-L), column bottom level (Col-L) and vapor flowrate at top column (Vap-In). From the observation, result of organic level (Org-L) and vapor flowrate (Vap-In) is not really satisfying where the response is so far from the setpoint value.

Then, the data response of the unsatisfying results is being developed in Neural Network control to see the improvement. In order to develop the result of the Neural Network control, the data of the process is trained and validated and the best result of the trained data is run back to the process to get the final result. The final result is compared and analysis to the previous result and the result is quite positive.

According to the results that have been developed, the objectives of the study are finally achieved. The Vinyl Acetate Monomer (VAC) process data has successfully generated and the performance of P, PI and Neural Network control are finally studied and investigated. The result of the study shows that the Neural Network control have the better quality of control element alongside P and PI control in this case study of Vinyl Acetate Monomer (VAC) process.

5.2 Recommendation

After completed the study, some improvement are discovered to be implemented in the future. Among room of improvement that can be done are:

- a) Online implementation of Neural Network Control is not applied in this study. To evaluate the efficiencies and robustness of the control, online implementation is more reliable.
- b) The case study of Vinyl Acetate Monomer (VAC) process did not run with the PID and the implementation of PID control has yet to be discovered.

REFERENCES

- Astrom, K. J., and T. Haggglund (1995), *PID Controllers: Theory, Design, and Tuning*, 2nd ed., ISA, Research Triangle Park, NC.
- Baughman, D., and Liu, Y. (1995). *Neural Networks in Bioprocessing and Chemical Engineering*, Academic Press, San Diego, CA.
- Dale E. Seborg, Thomas F. Edgar, and Duncan A. Mellichamp (2004), *Process Dynamic and Control*.
- Downs, J.J and E.F. Vogel (1993), A plant-wide industrial process control problem, *Computers Chem. Engng* 17 245-255.
- George Stephanopoulos (2004), *Chemical Process Control An Introduction to Theory and Practice*, Department of Chemical Engineering, Massachusetts Institute of Technology.
- Haykin, S. S. (1999), *Neural Networks: A Comprehensive Foundation*, 2nd ed., Prentice-Hall, Upper Saddle River, NJ.
- Luyben, M.; Tyreus, B. (1998), *An Industrial Design/Control Study for the Vinyl Acetate Monomer Process*, *Computers Chem. Engng.* 22, 867.
- McMillan, G. K., (1994), *Tuning and Control Loop Performance*, 3rd ed., ISA, Research Triangle Park, NC.
- Michael L. Luyben and Bjorn D. Tyrues (1997), *An Industrial Design/Control Study for the Vinyl Acetate Monomer Process*, DuPont Central Research & Development, Experimental Station, Wilmington, DE.
- Psichogios, D. C., and L. H. Ungar (1991), *Direct and Indirect Model Based Control Using Artificial Neural Networks*, *Ind. Eng. Chem. Res.*

Rong Chen, Kedar Dave and Thomas Mc Avoy (1998), *A Nonlinear Dynamic Model of a Vinyl Acetate Process*, Department of Chemical Engineering/Institute for Systems Research, University of Maryland, College Park.

Shinskey, F. G.(1996), *Process Control Systems*, 4th ed., McGraw-Hill, New York.

Su, H. T., and T.J. McAvoy (1997), *Artificial Neural Network for Nonlinear Process Identification and Control*, 2nd ed., Prentice Hall, Upper Saddle River, NJ.

Y. Lee, S. Park, M. Lee, C. Brosilow (1998), *PID Controller Tuning for Desired Closed-loop Responses for SI/SO Systems*, AICHE J.

APPENDIX A1

MAIN PROGRAM FOR DATA GENERATION FOR VINYL ACETATE PROCESS

```

function test_VAcPlant(minute,selected_ID)

%MV24: Column Bottom Exit is used to control the Column Bottom Level
SP_ColButtom=0.5;
K_ColButtom=0;
Ti_ColButtom=100;
act_ColButtom=-1;
mode_ColButtom=1;
Ponly_ColButtom=1;
ht_ColButtom=1/transmitter_sampling_frequency(25);
hc_ColButtom=1/controller_sampling_frequency(25);
uLO_ColButtom=0;
uHI_ColButtom=4.536;
ded_ColButtom=transmitter_deadtime(25);
tau_ColButtom=transmitter_lag;
yLO_ColButtom=0;
yHI_ColButtom=1;
Nded_ColButtom=1+transmitter_deadtime(25)*transmitter_sampling_frequency(25)
;
Ntau_ColButtom=1;
xxx_ColButtom(1)= (y_ss(21)-yLO_ColButtom) / (yHI_ColButtom -
yLO_ColButtom);
for i=2:Nded_ColButtom
xxx_ColButtom(i)= xxx_ColButtom(1);
end
for i=1:Ntau_ColButtom
yyy_ColButtom(i)= xxx_ColButtom(Nded_ColButtom);
end
xi_ColButtom= (MVs(25) - uLO_ColButtom) / (uHI_ColButtom - uLO_ColButtom)-
K_ColButtom*act_ColButtom*((SP_ColButtom-
yLO_ColButtom)/(yHI_ColButtom-yLO_ColButtom)-
yyy_ColButtom(Ntau_ColButtom));

function Transient_Plot(y_history,u_history,setpoint,my_label,MV_label,sampling)
warning off
k_y=(size(y_history,1)-1)*sampling; %ending minute

```

```
k_u=(size(u_history,1)-1)*sampling; %ending minute
y_lowlimit=[0.07,118,0,0.65,118,100,150,0,30,10,50,0,0,0,0,0,0.2,120,0.05,108,0,0,0,0];
y_highlimit=[0.08,132,1,0.75,132,200,170,1,50,20,100,1,20,50,1,50,0.02,0.35,140,0.30,112,1,1,1,4];
figure(9);
for i=20:25
subplot(4,2,i-19);
plot(0:sampling:k_y,y_history(:,i));
if i<=size(setpoint,1)
hold on
plot(0:k_y,setpoint(i)*[ones(1,k_y),1],':r');
hold off
end
ylabel(my_label(i,:));
xlabel('minute')
```

APPENDIX A2

SUBFUNCTION FOR DATA PREPARATION

```

clc;
clear;

function [input,output,vinput,voutput,X]=mdata

load databaru2.mat
[c,d]=size(y_history);

% mean-centering and variance-scaling data

for j=1:d-1,i=1:c
mdata(i,j)=y_history(i,j)-mean(y_history(:,j));
msdata(j,i)=mdata(i,j)/std(y_history(:,j));

% msdatad(j,1:c-1)=msdata(j,2:c);
end

X=(c/2)-1;

% training data

input(1,1:X)=msdata(1,1:X);
input(2,1:X)=msdata(2,1:X);
input(3,1:X)=msdata(3,1:X);

% input(4,1:X)=msdatad(1,1:X);
% input(5,1:X)=msdatad(2,1:X);
% input(6,1:X)=msdatad(3,1:X);

output(1,1:X)=msdata(4,1:X);

% cross-validation data

vinput(1,1:X)=msdata(1,X+1:2*X);
vinput(2,1:X)=msdata(2,X+1:2*X);
vinput(3,1:X)=msdata(3,X+1:2*X);

% vinput(4,1:X)=msdatad(1,X+1:2*X);

```

```

% vinput(5,1:X)=msdatad(2,X+1:2*X);
% vinput(6,1:X)=msdatad(3,X+1:2*X);

voutput(1,1:X)=msdata(4,X+1:2*X);

function [Tinput,Toutput,X,min,max]=dprepT
%DPREPT
%-----
% This subfunction creates data for training and cross-validation
%
% input,output = training data
% vinput,voutput = cross-validation data
[datas,p,min,max]=dscale;
X=p;

% Cross-validation data
Tinput(1,1:X)=datas(1,1:X); % Reflux flowrate
Tinput(2,1:X)=datas(2,1:X); % Condenser flowrate
Tinput(3,1:X)=datas(3,1:X); % Pumparound return flowrate
Tinput(4,1:X)=datas(4,1:X); % Top stage temperature
Tinput(5,1:X)=datas(5,1:X); % Distillate flowrate
Tinput(6,1:X)=datas(6,1:X); % Bottom flowrate
Tinput(7,1:X)=datas(7,1:X); % Feed flowrate
Toutput(1,1:X)=datas(8,1:X); % Top stage pressure
Toutput(2,1:X)=datas(9,1:X); % Bottom stage temperature
% Toutput(3,1:X)=datas(10,1:X); % C8 flowrate

```


APPENDIX A3

SUBFUNCTION FOR DATA SCALING

```

function [datas,p,min,max]=dscale
%DSCALE
%-----
% This subfunction scales data to value between 0 and 1
%
% datas = scaled data
% data = actual data before scaling
% min = actual data at their minimum
% max = actual data at their maximum
load databaru2.mat;
input=y_history;
[r,m]=size(input);
refl=input(:,3); % Reflux flowrate
cond=input(:,4); % Condenser flowrate
pump=input(:,5); % Pumparound return flowrate
toptemp=input(:,6); % Top Stage Temperature
dist=input(:,7); % Distillate flowrate
bott=input(:,8); % Bottom flowrate
feed=input(:,9); % Feed flowrate
toppres=input(:,10); % Top stage pressure
bottemp=input(:,11); % Bottom stage temperature
C8=input(:,12); % C8 flowrate
j=r;
for i=1:r
j=j-1;
dataq(1,i)=refl(j);
dataq(2,i)=cond(j);
dataq(3,i)=pump(j);
dataq(4,i)=toptemp(j);
dataq(5,i)=dist(j);
dataq(6,i)=bott(j);
dataq(7,i)=feed(j);
dataq(8,i)=toppres(j);
dataq(9,i)=bottemp(j);
dataq(10,i)=C8(j);
r=r-1;
end

```

```
[n,p]=size(dataq);
for i=1:n
max(i)=dataq(i,1);
min(i)=dataq(i,1);
for j=1:p
if dataq(i,j)>max(i)
max(i)=dataq(i,j);
end
if dataq(i,j)<min(i)
min(i)=dataq(i,j);
end
end
datas(i,:)=(dataq(i,:)-min(i))/(max(i)-min(i));
% datad(i,1:p-1)=datas(i,2:p); % 1 delayed term
% datad1(i,1:p-2)=datas(i,3:p); % 2 delayed term
end
```

APPENDIX A4

MAIN PROGRAM FOR TRAINING OF PROCESS PREDICTOR

```

% clc;
% clear;
% [datas,p,min,max]=dscale
[input,output,X,min,max]=dprep;
[Vinput,Voutput,X,min,max]=dprepV;
[Tinput,Toutput,X,min,max]=dprepT;
ptr=input; ttr=input(1,:); % Training
v.P=Vinput; v.T=Vinput(1,:); % Validation
t.P=Tinput; t.T=Tinput(1,:); % Testing
S1=30; % Number of nodes
net1=newelm(minmax(input),[S1 1],{'tansig' 'purelin'},'trainlm');
net1.trainparam.epochs=500; % Max epoch number
net1.trainParam.goal=1e-8;
net1.trainParam.max_fail=10;
net1.trainParam.show=5;
net1=init(net1);
[net1,tr]=train(net1,ptr,ttr,[],[],v,t);
an1=sim(net1,input);
error=an1-input(1,:);
trainmse=sumsqr(error)/X;
Van1=sim(net1,Vinput);
valmse=sumsqr(Van1-Vinput(1,:))/X;
Tan1=sim(net1,Tinput);
testmse=sumsqr(Tan1-Tinput(1,:))/X;
fprintf('TrainMSE=%e, ValMSE=%e, TestMSE=%e\n',trainmse,valmse,testmse);
time=1:X;
figure(1)
subplot(2,1,1),plot(time,an1,'r',time,input(1,:),'b');
ylabel('Pressure, kPa');
title('Top Column Pressure Predictor (Training)')
subplot(2,1,2),plot(time,Van1,'r',time,Vinput(1,:),'b');
ylabel('Pressure, kPa');
title('Top Column Pressure Predictor (Validation)')
legend ('Actual','Predicted',4)
save net1.mat

```