[MODELING OF PH NEUTRALIZATION PROCESS PILOT PLANT]

By

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FINAL REPORT

Submitted to the
Electrical & Electronics Engineering Programme
in partial fulfillment of the requirements for the
BACHELOR OF ENGINEERING (Hons)
(ELECTRICAL AND ELECTRONICS ENGINEERING)

November 2004

Universiti Teknologi PETRONAS
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CERTIFICATION OF APPROVAL

MODELLING OF PH NEUTRALIZATION PROCESS PILOT PLANT

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Faridah bt Hassan

A project dissertation submitted to the
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Approved by,

....
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CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original is my own except as specified in the references and acknowledgements, and the original work contained herein have not been undertaken or done by unspecified sources or persons.

....

(FARIDAH BT HASSAN)

ABSTRACT

System Identification is an art of constructing a mathematical model for a dynamic response system. The modeling process is based on the observed input and output data for a system. To start a modeling process, a good understanding of process behavior is required as it will determine the important parameters and characteristics to be analyzed.

pH neutralization is a very nonlinear process. It is not easy to get an accurate model as compared to the actual model. Modeling using conventional methods does not seem to give a reliable model for this process. Thus, for wide a range of neutralization pH values, conventional modeling methods are not sufficient. Therefore, for this project, intelligent approaches are considered.

The conventional methods that are used by the Author are mathematical modeling, empirical modeling and statistical modeling. Mathematical modeling is done to see the relation of inputs and output. Empirical modeling is the common method used for plant modeling. Statistical modeling is more a to computerized modeling where it requires a good computer configuration basic in order to achieve the desired output. Neural Network is used for the intelligent method. Neural network is an intelligent approach that has the capability to predict future plant performance by training several datasets.

These conventional and intelligent methods are compared between each other in term of the model accuracy, model reliability and flexibility. Modeling using mathematical modeling is tedious and requires more effort on the block diagram configuration in order to get an accurate result. Empirical modeling is basically good enough for plant identification, unfortunately for a highly nonlinear system, the method does not seem reliable. Statistical modeling has the ability to predict an acceptable higher order model. On top of that, neural network could give a more reliable and accurate result.

ACKNOWLEDGMENT

In the name of ALLAH, the Most Graceful and Most Merciful,

First, I would like to express my greatest gratitude to my supervisor, Ms Suhaila Badarol Hisham and my ex-supervisor, Mr Rosdiazli Ibrahim, for their expert guidance, attention and suggestions, supports and advices regarding the project and difficulties faced during the project execution.

My honorable thanks to Mr Abdul Aziz Ahmad, the Staff Engineer/ Instrument & Systems Engineer of PETRONAS Fertilizer Kedah Sdn Bhd, and Mr. Mohd Isa b Othman, Assistant Superintendent of PETRONAS Dagangan Berhad, for their support, encouragement, whose competence and kindness enabled me to concentrate on my work

Special thanks to the Instrumentation and Control lab technician, Mr. Azhar bin Zainal Abidin and Mr. Nasir from Chemical Engineering department for their guidance, supports and concern during the project works.

Not forget to mention, I am grateful to my beloved friends, Mr. Azmin bin Ishak (EE), Ms Siti Farhana bt Mohd Shaari (CE), Mr. Khairul Anwar Idris (EE) and Ms Nazatul Sheema Che Din (CE) because of given freely of their time and knowledge to discuss together in improving materials of my project.

To my family, love and thank you. Without your enormous support and concern, all my effort in preparing this final year project would have not successful.

Last but not least, my appreciation goes out to the individuals or groups that have helped me in any possible way to complete this project.

Above all, I would like to thank God for making this project's accomplishment a reality.

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ABBREVIATIONS AND NOMENCLATURES

CSTR	Continuous Stirred Tank Reactor
GUI	Graphical User Interface
AT	pH Transmitter
AIC	pH Controller
FT	Flow Transmitter
CT	Conductivity Transmitter
P	Pump
HV	Hand Valve
M	Motor
AG	Agitator
FCV	Flow Control Valve
VE	Vessel
MNGR	Manager mode
DCS	Distributed Control System
UTP	Universiti Teknologi PETRONAS
SP	Set Point
PV	Process Variable
MV	Manipulated Variable
PRC	Process Reaction Curve
H_2SO_4	Sulfuric Acid
NaOH	Natrium Hydroxide
SASB	Strong Acid Strong Base

CHAPTER 1
INTRODUCTION

1.1. Background of Study

Modeling refers to a process of deducing a mathematical model of a dynamic response based on the behavior of input and output from observed dataset. This requires good estimation methods for system identification of the dynamical systems. Modeling is primarily important to validate the system performance. Good modeling is considered as performing well in accuracy, reliability and flexibility.

This project is conducted on a pH control pilot plant for pH system identification. Several real-time datasets are taken from the plant experiment and the modeling part is done using several modeling approaches. The conventional modeling approaches used to identify the system are the mathematical modeling, empirical modeling and statistical modeling. Intelligent modeling is a major consideration for this project where neural network using feedforward backpropagation network technique is used to model the system based on the actual datasets from plant experiment.

1.2. Problem Identification

pH neutralization is a highly nonlinear process and needs a reliable method to achieve model optimization. Thus for wide range of neutralization pH values, conventional modeling methods are insufficient.

Therefore, modeling of pH neutralization process using several intelligent approaches is considered.

1.3 Significance of the Project

Generally, the outcome of this investigation serves as base information for modeling pH neutralization using conventional methods and intelligent approach. The conventional methods implemented for the pH pilot plant modeling will be later compared to the intelligent modeling approaches in term of reliability, feasibility and accuracy.

In summary, this project can be considered as an educational tool to familiarize oneself with plant activities. Analysis on modeling using several approaches is also a beneficial step to enhance plant process control.

1.4 Objective of Study

1.4.1 To obtain a model for pH Neutralization process pilot plant based on several methods.

- Using conventional methods such as mathematical, empirical and statistical methods
- Using intelligent approach which is Neural Networks

1.4.2 To make comparison between conventional and intelligent approach in terms of flexibility, reliability and accuracy.

1.5 Scope of Study

The scope of this intelligent plant process control project is narrowed down to a single loop of pH control, AIC-122, for the product of Control Stirred Tank Reactor (CSTR) at the UTP pilot plant. The plant controls the pH reaction of strong acid strong base solutions (SASB). The strong acid solution used is *Sulfuric Acid* (H_2SO_4) and the strong alkaline solution used is *Natrium Hydroxide* (NaOH).

The modeling part of the project uses conventional methods such as mathematical, empirical and statistical methods. Mathematical model needs more parameters detail compared to empirical model since it involves with more calculations. On top of that, intelligent approach such as neural networks is also used for the pH system identification.

Comparison is made between recorded real-time data from plant experiment and simulation from MATLAB-Simulink. Thus, comparison between conventional and intelligent approach in terms of flexibility, reliability and accuracy can be made. The accuracy of the model will be observed based on how resembles the predicted model to the actual output reaction.

1.5 The Relevancy of the Project

A good model prediction is important especially during systems performance test. Inaccurate model will give effects during tuning where it is difficult to tune the output to the desired set point.

Modeling using conventional methods is not compatible for a highly nonlinear system like pH neutralization process. A lot of research has been done on the application of intelligent approaches for process control throughout the past few years. In most cases, the outcomes are very promising for the control applications. Besides having the intelligent approaches as new and reliable control techniques, modeling using intelligent approach such as neural network is believed would give a better model prediction than using conventional methods.

1.6 Feasibility of the Project within the Scope and Time Frame

The expected achievements by the end of Semester July 2004 involve with the modeling of pH neutralization for process control. The plant experiment is done at pH control pilot plant in Instrumentation & Control Laboratory of Universiti Teknologi PETRONAS (UTP).

Many samples of data have been collected. For a start, proper experimental design is required so that the shape, duration and base operating condition of the pH control system can be determined. Therefore, longer duration time is needed for real-time data gathering. It took about half of the semester to for this purpose.

The datasets are then analyzed using several modeling methods. For modeling simulation, the datasets are extracted to MATLAB/Simulink software for complement investigation. Software simulation also required quite a long time for results accomplishment.

CHAPTER 2

LITERATURE REVIEW AND/ OR THEORY

2.1 The pH Scale

pH is defined as log10[H^+] and is a measure of the acidic and basic of an aqueous solution. Aqueous solution contains the proportion of water. The pH is scaled from 1 to 14. A value of pH lower than 7 is designated as acidic solution whereas the value of pH upper than 7 is designated basic or alkaline. Whereby, neutralization is the process to neutralize acidic and basic solution into salt and water which falls into pH 7 in the pH scale [2].

The chemistry of an aqueous solution often depends critically on the pH of the solution. It is therefore important to examine how the pH of solutions relates to the concentration of acids and bases. The case for this pH control pilot plant involves strong acid and strong base (SASB). Strong acid and base are strong electrolytes, existing in aqueous solution entirely as ions.

2.2 Titration Curves

Generally, a typical curve titration curve obtained by titrating an acid with a base. All curves start out with a very slow, or moderate, change in pH while the base is being added to the acid. As the titration continues and the endpoint is approached, the pH of the solution will start to change more dramatically. At the endpoint, the line changes most dramatically. Once the endpoint has been passed, the rate of pH change diminishes again. It will resemble the first part of the graph except at a higher pH value.

The midpoint of the most vertical part of the graph will correspond to the exact endpoint. This will also correspond to the equivalence point, or the point at which the equivalents of acid equals the equivalents of base. In addition, the midpoint will also determine the pH of the salt that was formed during the titration.

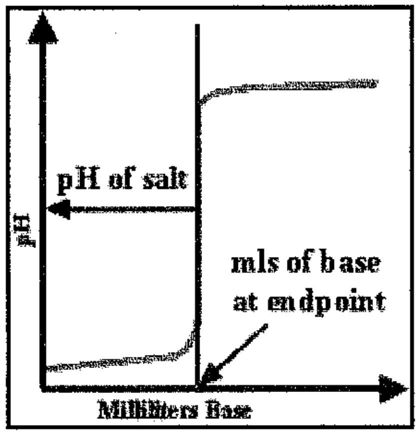

Figure 2.1: A typical titration curve of acid influence to basic solution.

Not all titration curves are exactly the same. The graphs will differ somewhat in shape, depending upon whether the acid that is being titrated is a strong acid or weak acid[4]. For strong acid with a strong base titration, there will be a single endpoint and the graph is nearly vertical at the endpoint. An acid with two protons will have two endpoints, one for each hydrogen. Unfortunately, the quality of the graph deteriorates at the successive endpoints[4]. In other words, the first endpoint is fairly obvious, the second endpoint is not as well defined.

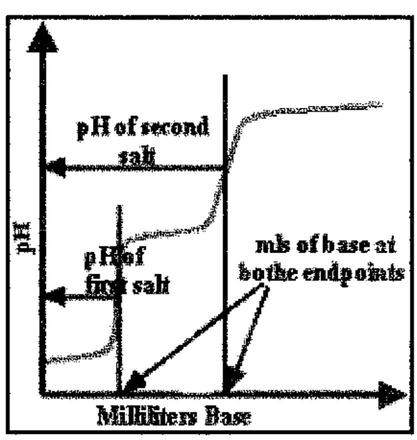

Figure 2.2: A titration curve of acid with two protons

2.3 pH Neutralization for Strong-Acid-Strong-Base (SASB)

Here is the theory of pH neutralization by Brown LeMay Bursten, where pH is the measurement of concentration of hydrogen ions, $H^+(aq)$ in an aqueous solution. The concentration of H^+ in aqueous solution is usually quite small, therefore usually express $[H^+]$ in terms of pH, which is defined as the negative logarithm in base of 10 of $[H^+]$ [2].

$$pH = -\log[H^+] \qquad (2.1)$$

The ion product of water in equilibrium constant expression is,

$$K_c = \frac{[H_3O^+][OH^-]}{[H_2O^+]^2} \qquad (2.2)$$

Rearrange equation 2.2,

$$K_c [H_2O^+]^2 = [H_3O^+][OH^-] \qquad (2.3)$$

The product of the two constants, K_c and $[H_2O]^2$, defines a new constant denoted by K_W, called the ion product constant for water [2]. At 25°C, K_w equals 1.0×10^{-14}. Thus, at 25°C,

$$K_w = [H_3O^+][OH] = 1.0 \times 10^{-14} \qquad (2.4)$$

Note: $[H_3O^+] = [H^+]$

From the fundamental theory of Bursten LeMay, McAvoy developed the equation characterizes the pH curve of the SASB reaction, which be noted as,

$$\mathrm{pH} = \log\sqrt{\frac{x^2}{4} + K_w} - \frac{x}{2} \quad \text{..(2.5)}$$

From the SASB equation, we can simulate the dynamic curve of pH neutralization via Simulink,

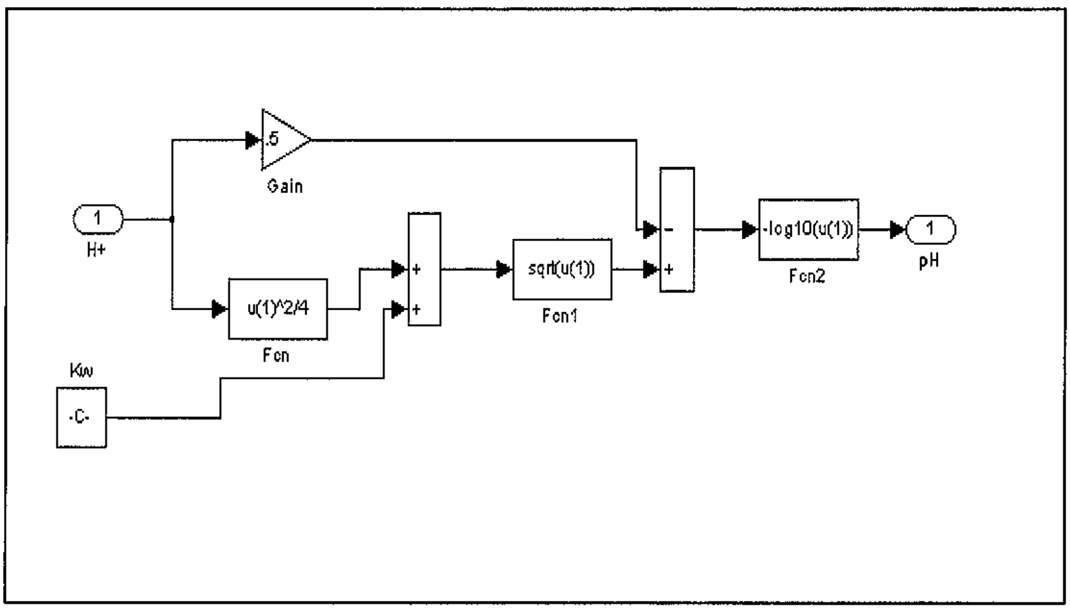

Figure2.3: SASB Simulink block diagram

2.4 The pH Control Pilot Plant

The schematic of P& ID diagram is shown in **Figure 2.4**. The acid solution is pumped from tank VE100 by pump P100 into Continuous Stirred Tank Reactor (CSTR) VE120. The alkaline solution from tank VE110 is pumped by pump P110 into the same CSTR. The CSTR is equipped with stirrer and pH transmitter AT-122. Desired neutralization process can be carried out in the second CSTR which flows from the downstream of VE120.

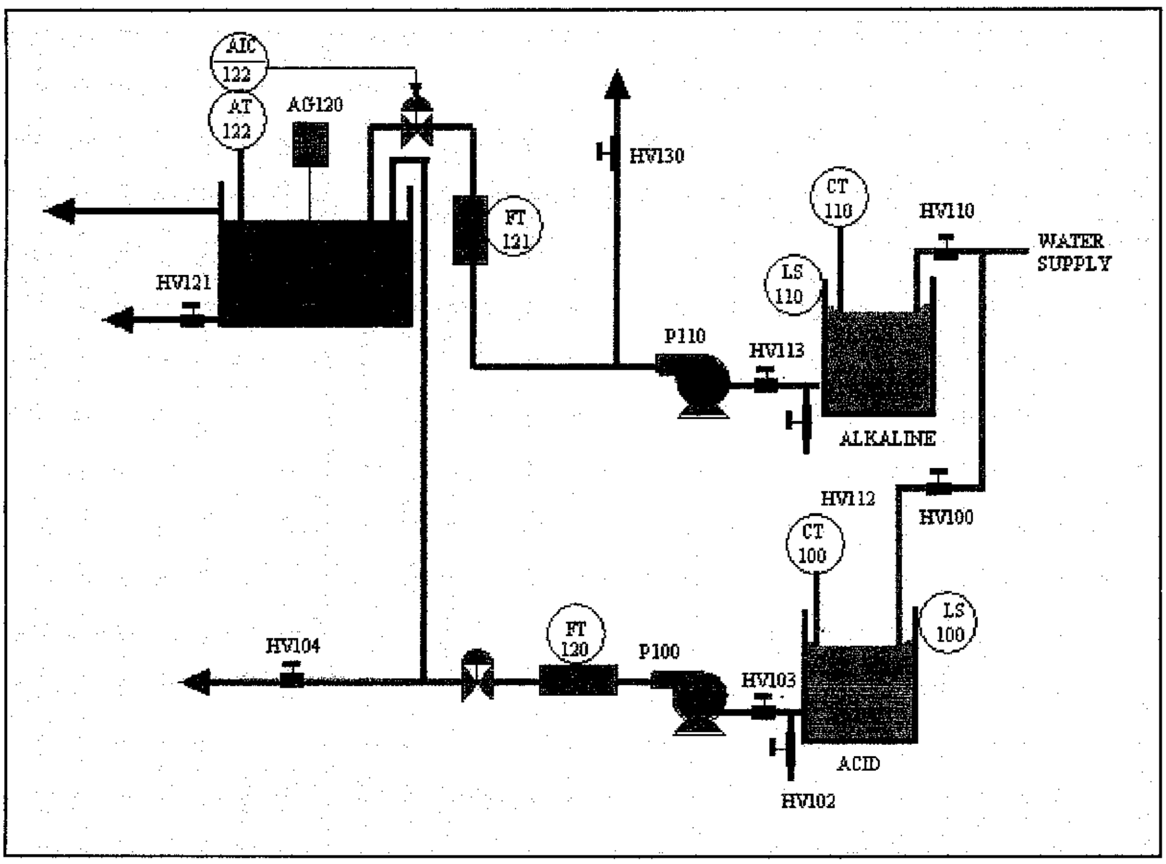

Figure 2.4: Piping & Instrumentation Diagram (P&ID)

2.5 Mathematical Model:

The mathematical approach is based on fundamental theories or laws, such as conservation of mass, energy and momentum. This approach is of favor because small number of principles can be used to explain a wide range of physical systems. In other words, this particular approach simplifies the view of nature. Apart from that, this approach has a broad range of applicability, which enables the task of evaluating potential changes in operating conditions and equipment and also to design new plants.

For the pH control reaction in a CSTR, the state space representation develop based on McAvoy et al [3],

$$V\frac{dx_a}{dt} = F_aC_a - (F_a + F_b)x_a \text{..........} (2.6)$$

$$V\frac{dx_b}{dt} = F_bC_b - (F_a + F_b)x_b \text{..........} (2.7)$$

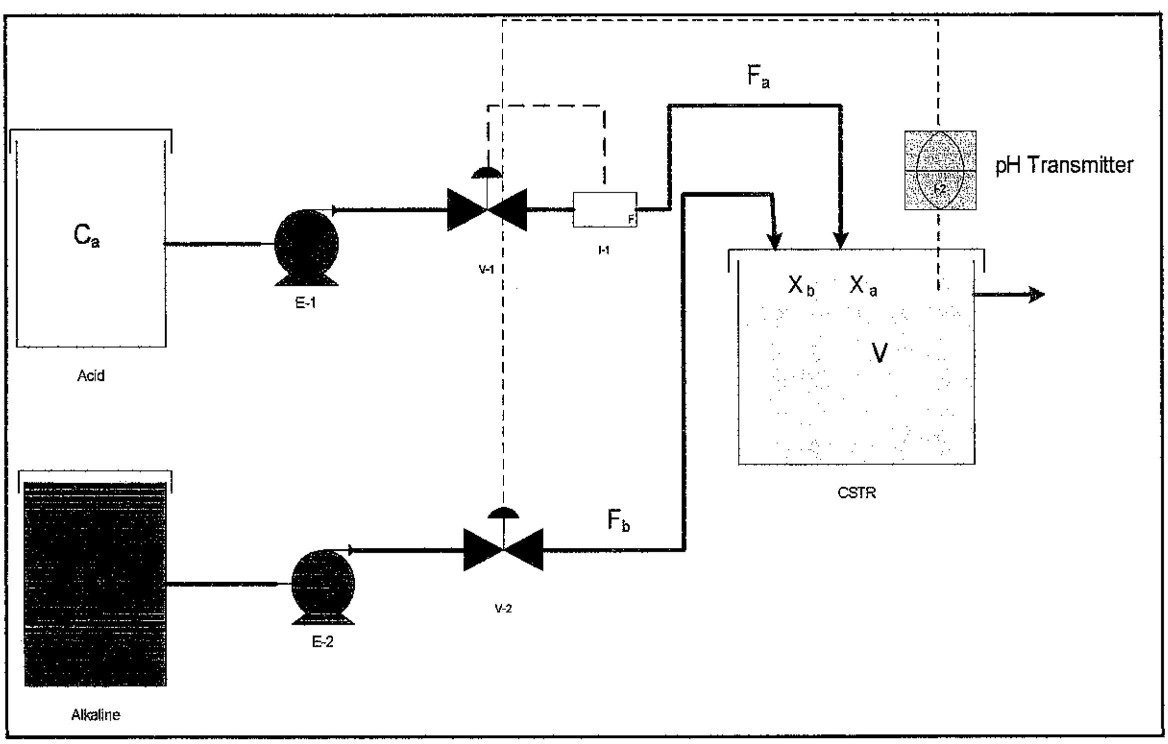

Figure 2.5: Physical representation of pH neutralization process.

McAvoy derived the dynamic model from experimental model which yields the state space representation of pH neutralization process,

$$\begin{bmatrix} \hat{x}_a \\ \hat{x}_b \end{bmatrix} = \begin{bmatrix} -F_a + F_b / V & 0 \\ 0 & -F_a + F_b / V \end{bmatrix} \begin{bmatrix} x_a \\ x_b \end{bmatrix} + \begin{bmatrix} F_a C_a / V \\ F_b C_b / V \end{bmatrix} u(t) \text{......(2.8)}$$

$$y = \begin{bmatrix} 1 & -1 \end{bmatrix} \begin{bmatrix} x_a \\ x_b \end{bmatrix} \text{.......(2.9)}$$

Where u(t) represents the inputs to the system which are F_a, F_b, C_a, and C_b

Note: x_a = Concentration of non reacting acid, mol/litre

x_b = Concentration of non reacting alkaline, mol/litre

C_a = Concentration of acid, mol/sec

C_b = Concentration of alkaline, mol/sec

F_a = Flow rate of acid, litre/sec

F_b = Flow rate of alkaline, litre/sec

V = Volume of CSTR, litre

From the state space representation of the pH control system, the systems of acid-base reaction block diagram represented as diagram below,

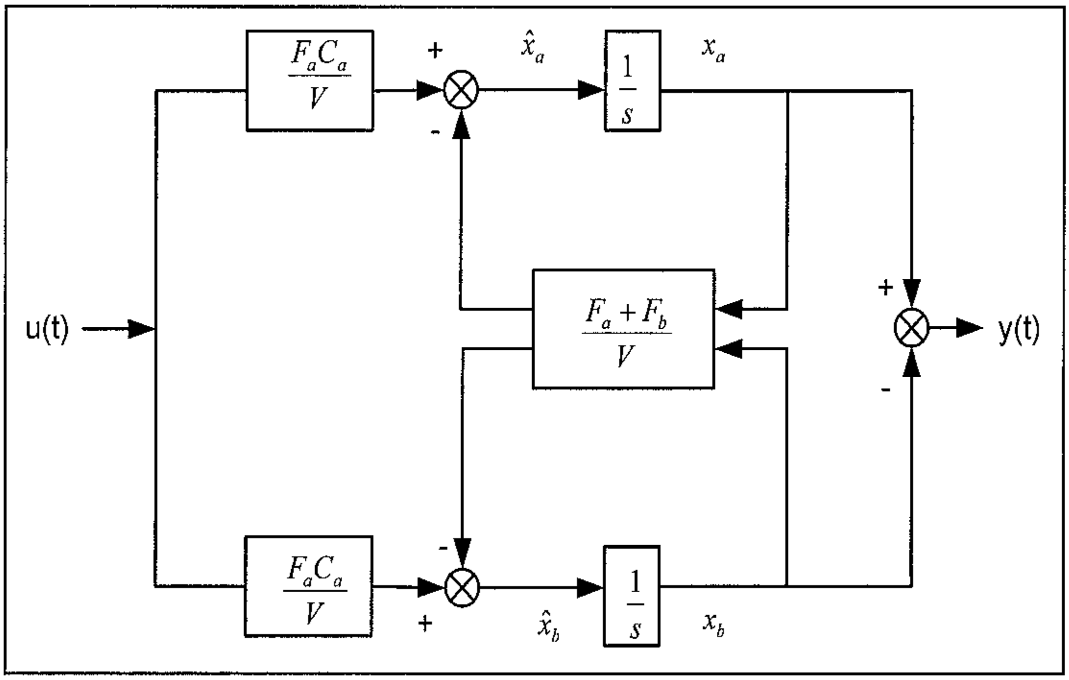

Figure2.6: pH control block diagram

2.6 Empirical Modeling

The purpose of plant modeling is to establish the relationships between parameters in the physical systems and the transient behavior of the systems.

Empirical modeling provides the dynamic relationship between selected input and output variables. Models are determined by making small changes in the input variable about nominal operating condition. The resulting dynamic response is used to determine the model. A linear transfer function developed using empirical methods are adequate for many process control designs and implementations.

The process reaction curve (PRC) employs simple graphical procedures for model fitting. In other words, the model is calculated by interpreting the graphical reaction curve. The graphical method has two major limitations which are first-order with dead time model and requires a perfect step input [1].

2.7 Statistical Model Identification

Statistical model identification methods provide more flexible approaches to identification that relate the model structure and experimental design. The statistical method employs desired principles for determining the parameters besides employing a tedious statistical method.

Statistical methods use all data and not just a few points from the response, which will provide better parameter estimation. The steps taken are similar to Empirical Modeling. In addition, Statistical methods involve the following actions [1];

- Introduce a perturbation (or sequence of perturbation) in the input variable. There is no restriction on the shape of the perturbation, but the effect on the output must be large enough to enable a model to be identified.
- Collect input and output response data.
- Calculate the model parameters via computer programming, eg. Matlab.

The basic idea is to formulate the model so that regression can be used to evaluate the parameters.

2.7.1 System Identification using ARMAX (Auto Regressive Moving Average with External Input)

System Identification using ARMAX can be considered as Statistical Method modeling. The mathematical models of a dynamic system can be built based on measured data. Essentially by adjusting parameters within a given model until its output coincides as well as possible with the measured output. The techniques can be applied to very general models. Most common models are difference equations descriptions, such as ARX and ARMAX models. ARMAX is chosen instead of AR and ARX because it has more parameters which will give advantages for ARMAX modeling.

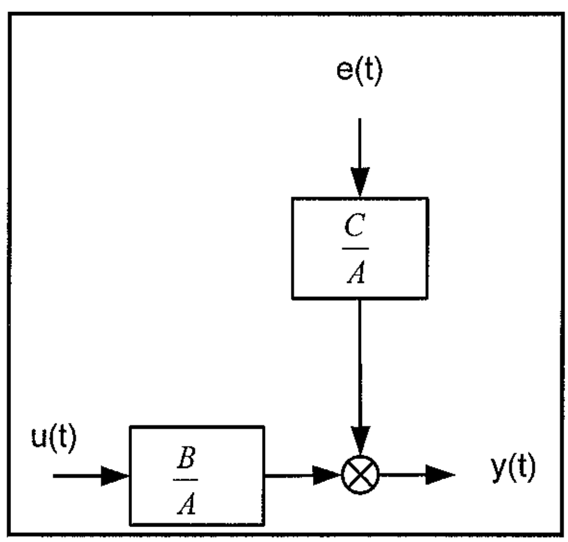

Figure 2.7: ARMAX model structure

For the ARMAX case, the model estimation involves an iterative, numerical search for the best fit [5]. There were different disturbance models are introduced.

A general input-output linear model for a single-output system with input u and output y can be written,

$$A(q)y(t) = \sum_{i=1}^{nu} [B_i(q)/F_i(q)]u_i(t-nk_i) + [C(q)/D(q)]e(t) \quad .(2.10)$$

Therefore, armax estimates the parameters of the ARMAX model structure,

$$A(q)y(t) = B(q)u(t-nk) + C(q)e(t) \quad \ldots\ldots(2.11)$$

using a prediction error method. The data contains the output-input data. Only time domain data are supported by armax [9]. The model orders can be specified as (...,'na',na,'nb',nb,...) or by setting the argument orders to

orders = [na nb nc nk] ....(2.12)

The parameters na, nb, and nc are the orders of the ARMAX model, and nk is the delay. Specifically,

$$na: \quad A(q) = 1 + a_1 q^{-1} + \ldots + a_{na} q^{-na} \quad \ldots\ldots(2.13)$$

$$nb: \quad B(q) = b_1 + b_2 q^{-1} + \ldots + b_{nb} q^{-nb+1} \quad \ldots\ldots(2.14)$$

$$nc: \quad C(q) = 1 + c_1 q^{-1} + \ldots + c_{nc} q^{-nc} \quad \ldots\ldots(2.15)$$

2.8 Neural Networks

Neural networks, inspired by biological nerves system, is a composed of simple element operating in parallel. Neural Network has the capability to predict future plant performance [5]. Neural network are adjusted or trained, so that a particular input leads to a specific target output.

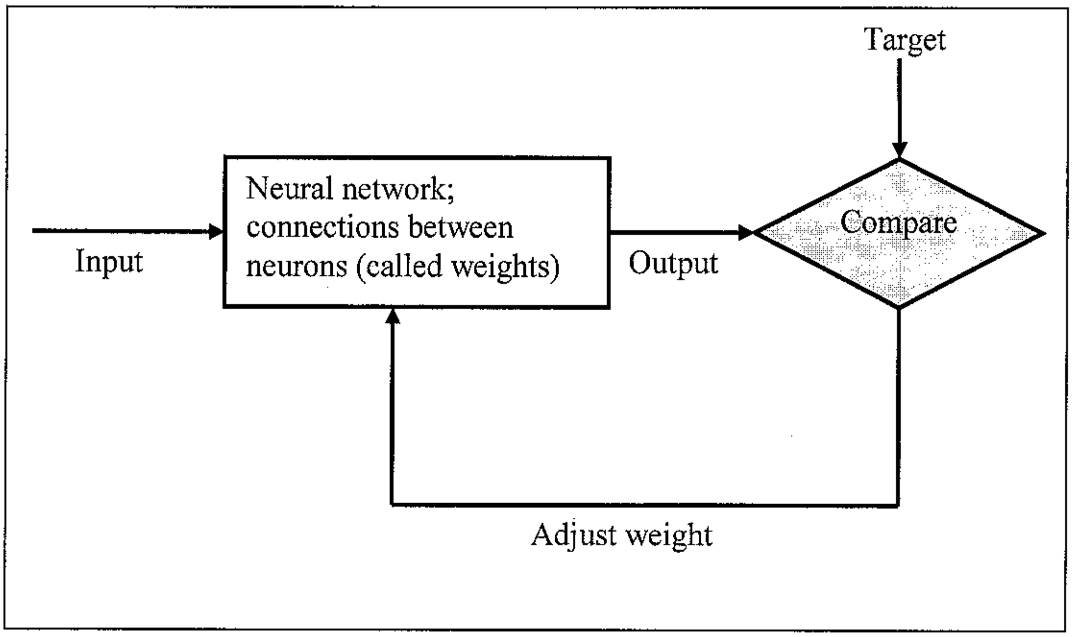

Figure2.8: Adjustment of neural network to obtain specific target output

Neural network performs two major functions which are learning and recall. Learning is the process of adapting the connection in neural network to produce a desired output vector in response to a stimulus vector presented in the input buffer [5]. Recall, on the other hand, is the process of accepting input stimulus and producing output response in accordance with the network weight structure. This condition occurs when a neural network globally output buffer.

Learning rules of neural computation indicates how connection weights are adjusted in response to a learning example. The most used learning rules in engineering application is supervised learning. In this method, the neural network is trained to give the desired response to a specific input stimulus. The difference between actual output and desired response constitutes an error which is used to adjust the connection weights.

2.81 Feedforward Backpropagation Network

A single-layer network of S logsig neurons having R inputs is shown below in full detail on the left and with a layer diagram on the right.

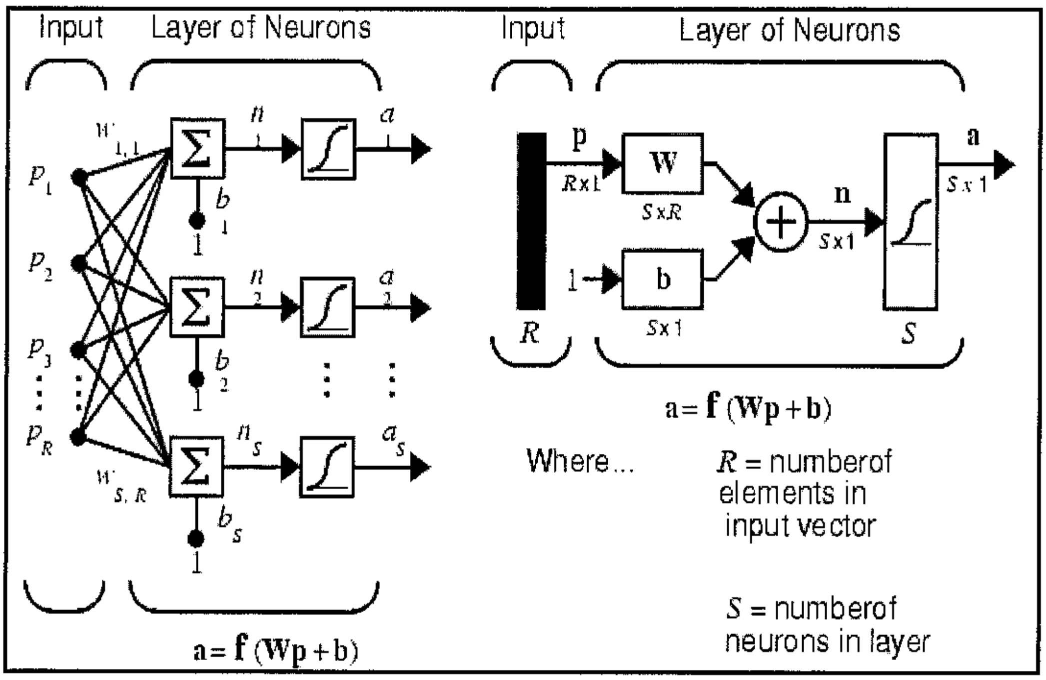

Figure 2.9: Layer of neurons

Feedforward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons [13]. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range -1 to +1.

Multiple-layer networks we used to determine the superscript on the weight matrices. The appropriate notation is used in the two-layer tansig/purelin network shown in **Figure 2.10**.

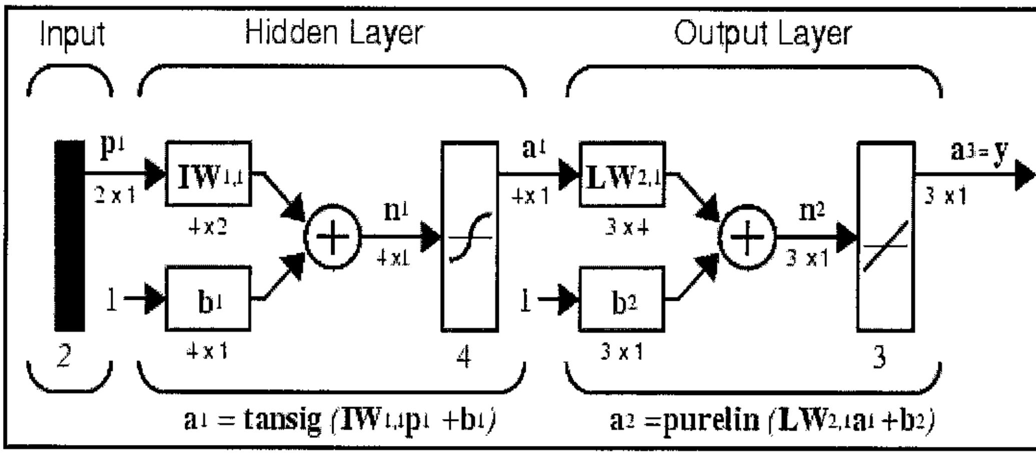

Figure 2.10: Two-layer feedforward backpropagation network

This network can be used as a general function approximator. It can approximate any function with a finite number of discontinuities, arbitrarily well, given sufficient neurons in the hidden layer [13].

CHAPTER 3
METHODOLOGY

3.1 Procedure Identification

3.1.1 Overall Project Flow

Generally, the identified steps procedure for modeling the pH control from pilot plant experiment to modeling simulation using various methods is shown in **Figure 3.1**. This flow chart is for overall steps configuration of this project.

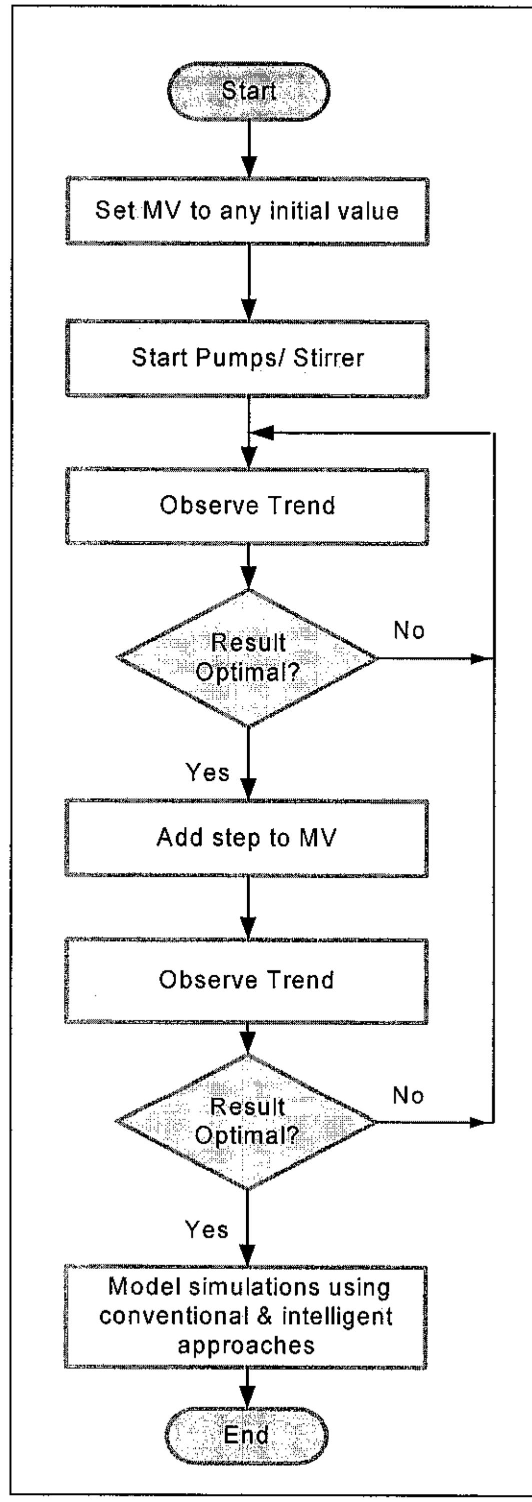

Figure 3.1: Overall flow diagram

3.1.2 Mathematical Modeling

Generally, according to Marlin, there are six steps procedure for mathematical modeling. First step is to define goals, which involves with functional relationships in this case the relationship of concentration acid and base in CSTR, with flow of acid and base, and volume of mixed solution in CSTR. Next is to prepare information for example by stating assumptions and data.

In order to formulate the model, the ordinary differential equation (ODE) of the system, which derived by McAvoy, is represented in state space representation.

During result analysis, result relationship is analysed between data and assumptions. Finally, the model is validated by comparing with experimental results.

The steps involve are shown in the flow chart in **Figure3.2.**

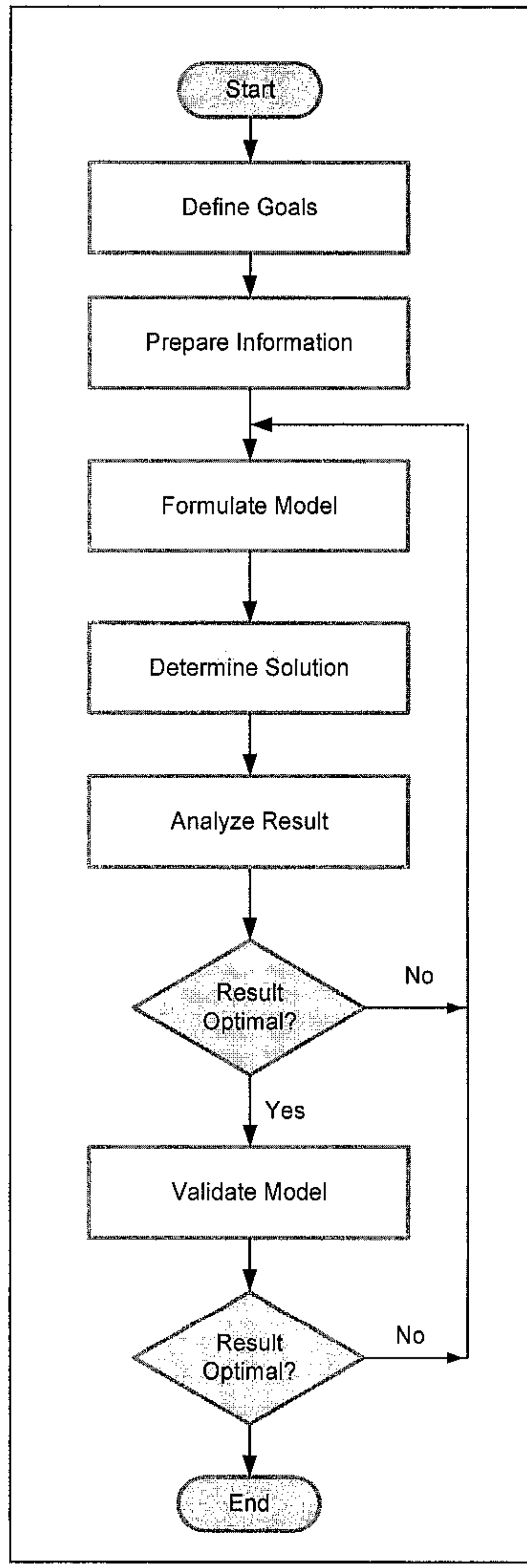

Figure 3.2: Mathematical modeling procedure

3.1.3 Empirical Modeling

An important aspect of empirical modeling is the need for proper experimental design. To determine model structure, many methods are available but initial structure is selected based on prior knowledge [1].

Generally the whole experiment will touch on several stages. The initial stage is to understand the P&I Diagram of the entire control loop as well as the process hook up and piping involved in the experiment.

There are six steps for developing empirical model of one system. The steps are shown in **Figure 3.3** below.

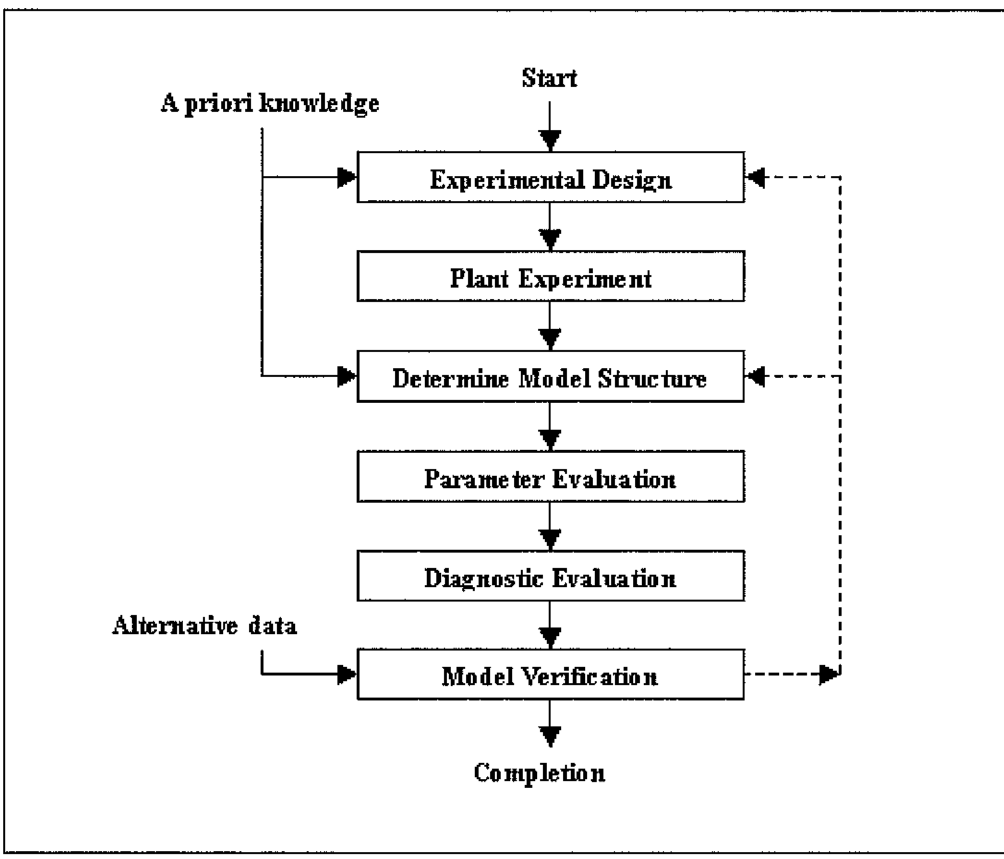

Figure 3.3: Procedure for Empirical Transfer Function Model Identification

For parameter estimation, two methods can be used which are the graphical technique calculation of Method I and Method II.

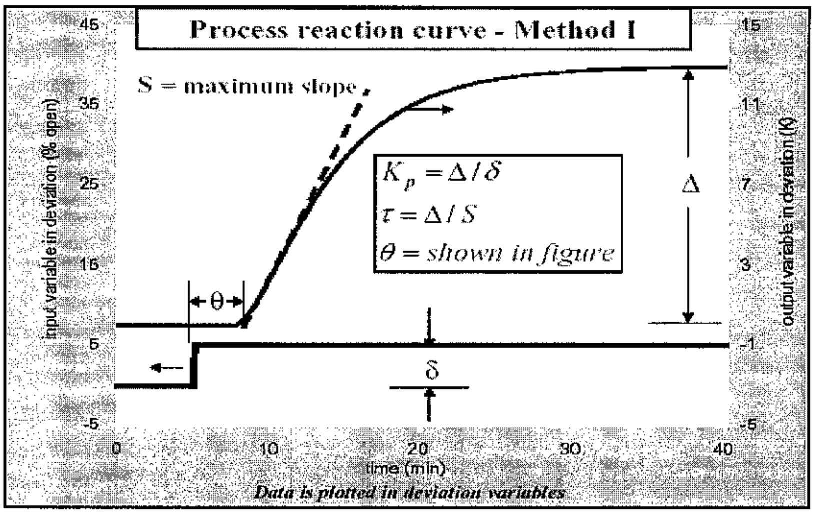

Figure 3.4a: Method I calculation

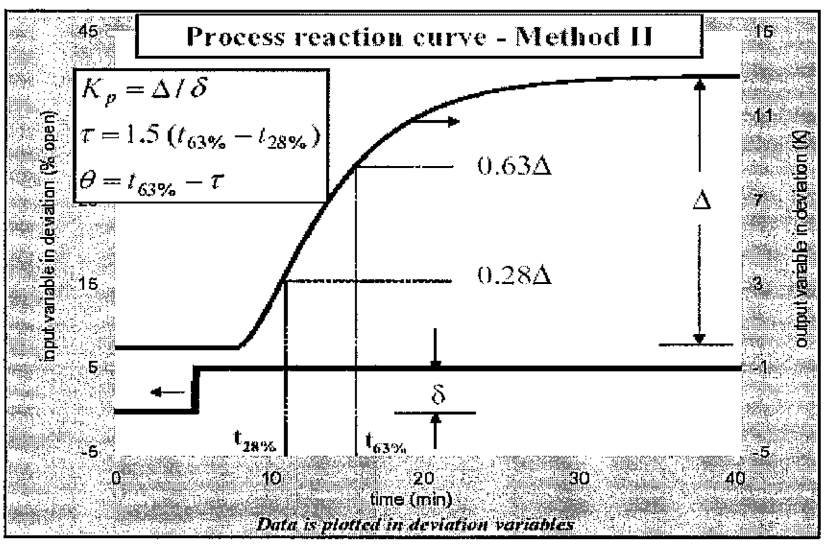

Figure 3.4b: Method II calculation

Diagnostic is the level of evaluation that determines how well the model fits the data used for parameter estimation. Finally, the model is compared with additional data not used in the parameter estimation for model verification.

3.1.4 Statistical Modeling (ARMAX)

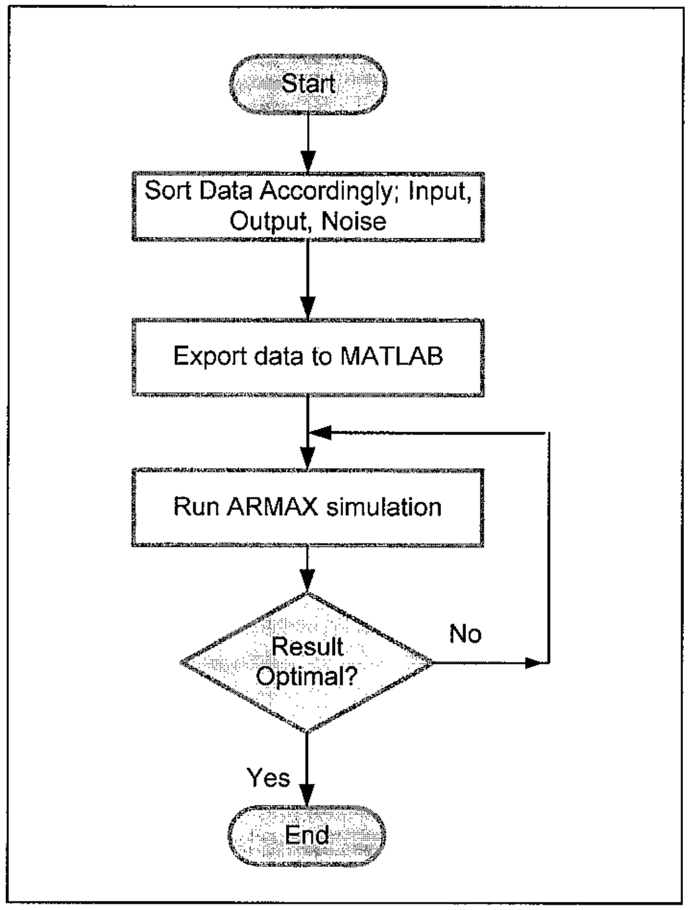

Figure 3.5: System Identification Flow Diagram

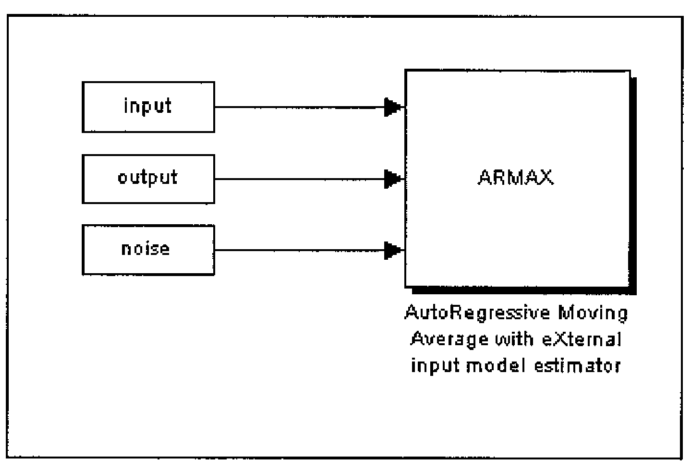

Figure 3.6 : ARMAX Simulink block diagram

3.1.5 Neural Network

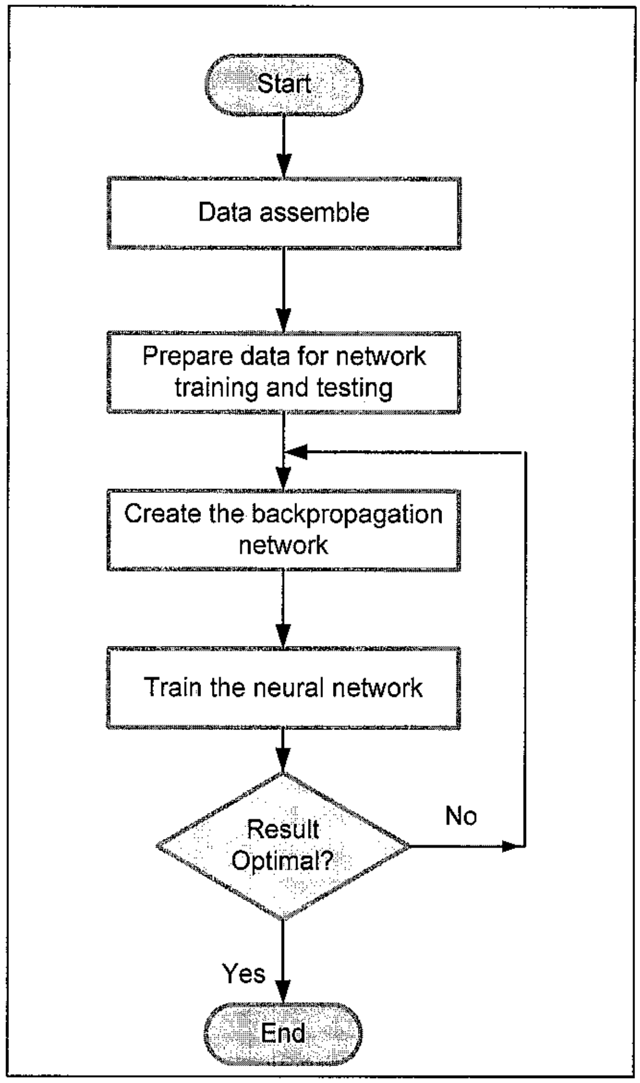

Figure 3.7: Neural Network flow diagram.

First of all, data is prepared for the network training. The real-time data that are obtained during lab experiments is assembled accordingly due to its input and output in MATLAB workspace.

Before training, it is necessary to scale the inputs and targets so that they always fall within a specified range. The function premnmx is used to scale inputs and targets so that they fall in the range [-1,1] [9]. The following code illustrates the use of premnmx function.

- *[pn,minp,maxp,tn,mint,maxt] = premnmx(input,target);*
- *net=train(net,pn,tn);*

The original network inputs and targets are in matrices form under the file named 'input' and 'target' respectively. The normalized inputs and targets, PN and TN, that are returned will all fall in the interval [-1,1]. The vectors minp and maxp contain the minimum and maximum values of the original inputs, and the vectors mint and maxt contain the minimum and maximum values of the original targets. After the network has been trained, these vectors will be used to transform the test data inputs that are applied to the network. They effectively become a part of the network, just like the network weights and biases [5].

Since premnmx is used to preprocess the training set data, then when the trained network is tested with new inputs they will be preprocessed with the minimum and maximums that were computed for the training set. This is accomplished with the routine tramnmx shown in the following code,

- *PN_Test=tramnmx(test_Ip,minp,maxp);*
- *TN_Test=sim(net,PN_Test);*
- *[queryInputs predictOutputs]=postmnmx(PN_Test,minp,maxp,TN_Test,mint,maxt);*

The function **newff** creates a feedforward network [5]. It requires four inputs and returns the network. The first input is a matrix of minimum and maximum elements of the input vector. The second input is an array containing the sizes of each layer. The third input is a cell array containing the names of the transfer functions to be used in each layer. The final input contains the name of the training function to be used. The following code explains the above descriptions.

- *net=newff(minmax(normalized_input),[size_of_layer],{transfer_function},'training_function');*

The Levenberg-Marquardt **(trainlm)** training function algorithm was designed to approach second-order training speed [5]. It also has a very efficient MATLAB implementation, since the solution of the matrix equation is a built-in function.

3.2 Tools and Software

3.2.1 (MATLAB-Simulink)

MATLAB offers array operations that allow one to quickly manipulate sets of data in a wide variety of ways. MATLAB also offers programming features similar to those of other computer programming languages. In addition, MATLAB offers graphical user interface (GUI) tools that allow one to use it as an application development tool [7]. Therefore, this project will utilize most of MATLAB programming application and its GUI development feature.

Simulink is an extension to MATLAB that allows engineers to rapidly and accurately build computer models of dynamic systems, using block diagram notation. With Simulink, it is easy to model complex nonlinear systems. Additionally, a Simulink model can produce graphical animations that show the progress of a simulation visually, significantly enhancing understanding of system behavior [8].

3.2.2 Honeywell Plantscape

Honeywell Plantscape is special software that is used for the server of the Distributive Control System (DCS) of the pH neutralization pilot plant. This software is slightly similar to the real plant DCS which is good enough to expose the users to the real plant applications. The server also provides a good database which really helpful for the data storage and configuration.

CHAPTER 4
RESULTS & DISCUSSION

4.1 Plant Experiment for System Identification

Several experiments have been done for model datasets validation. The process reaction curve (PRC) obtained are observed in terms of delay time (T_d), time constant (τ) and the change of ultimate value (Δ) of the graph for the output, also known as process variable (PV). Besides, the other important element under consideration during plant identification is the input perturbation step. This small perturbation step refers to the manually applied manipulative variable (MV). This is necessary to get the dynamic response in nominal operating conditions.

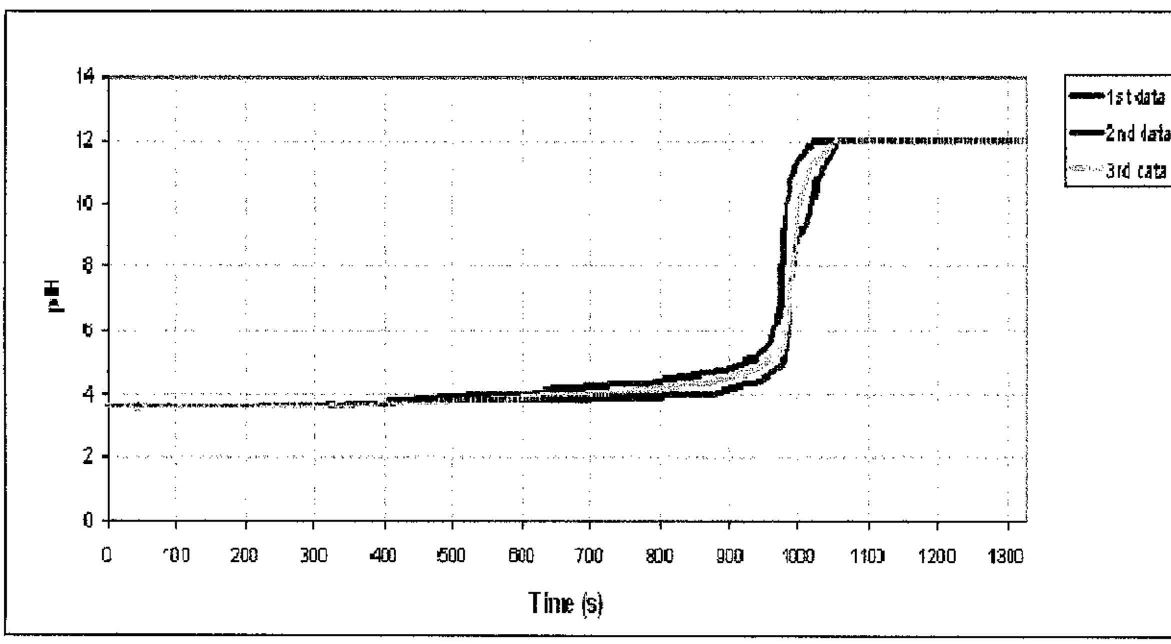

Figure 4.1: Comparison of 3 data sets from plant experiments

Figure 4.1 shows three validated data of pH neutralization model obtained from plant experiment. These datasets are approximately identical to each other. The curves start out with a very slow, or moderate, change in pH and fulfill the requirements of an SASB reaction where it has the steep rise at the endpoint. At the endpoint, the line changes most dramatically. Once the endpoint has been reached, the rate of pH change diminishes again. The reaction change slows down at an alkaline pH value which yields from values of 10 to 14.

The midpoint of the most vertical part of the graph corresponds to the equivalence point, or the point at which the equivalents of acid equals the equivalents of base. In addition, the midpoint will also determine the pH of the salt that was formed during the titration.

Data 2 has slightly a different curve shape than the other two datasets. This is because of H_2SO_4 has two protons that results for two endpoints; one for each hydrogen. Thus the quality of the graph deteriorates at the successive endpoints. Unlike Data 2, for Data 1 and Data 3, the graphs rise very steeply but nonetheless still can be considered as an SASB reaction.

4.2 Mathematical Modelling

The plant model using mathematical simulation is modelled based on the McAvoy derivation for strong acid and strong base pH neutralization. In general, the basic block diagram of pH control developed using mathematical model method and MATLAB Simulink software is as shown in **Figure 4.2** below. The configuration of inputs and outputs are made by referring to the actual pilot plant. It has five inputs and one output. The inputs are:

C_a = Concentration of acid, mol/sec

C_b = Concentration of alkaline, mol/sec

F_a = Flow rate of acid, litre/sec

F_b = Flow rate of alkaline, litre/sec

V = Volume of CSTR, litre

The output is the summation of non-reacting concentration of acid and alkaline which yields the pH value of the solution inside CSTR.

The plant transfer function which is represented in a matrix form or state space representation as shown in equation (2.8) and (2.9), is simulated via MATLAB Simulink shown in **Figure 4.2. Figure 4.3** shows the components masked inside the pH control plant model block.

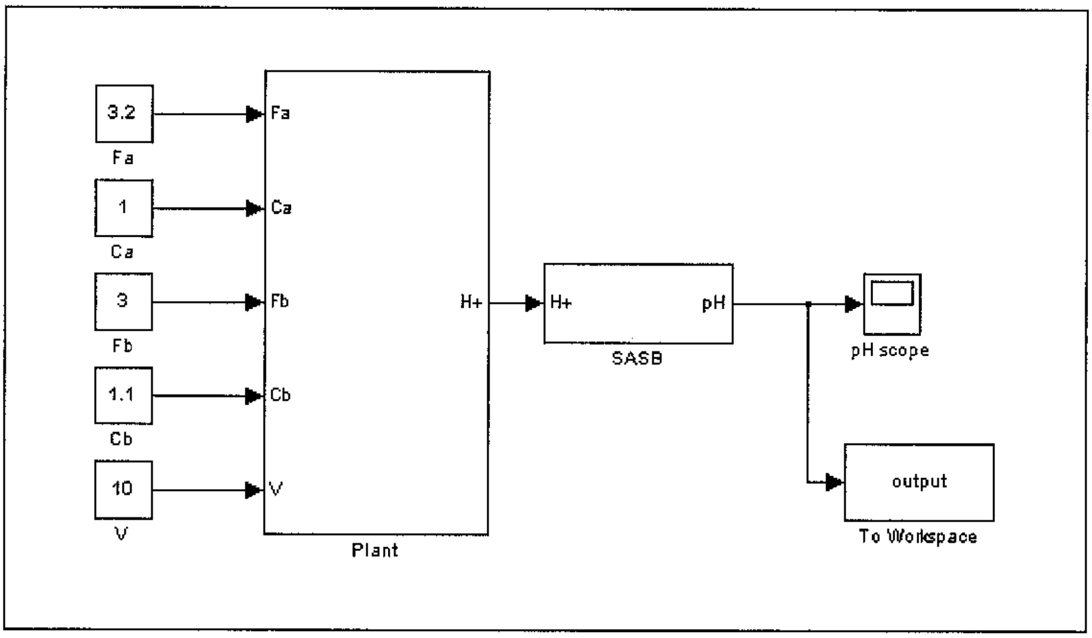

Figure 4.2: Mathematical model simulation block diagram

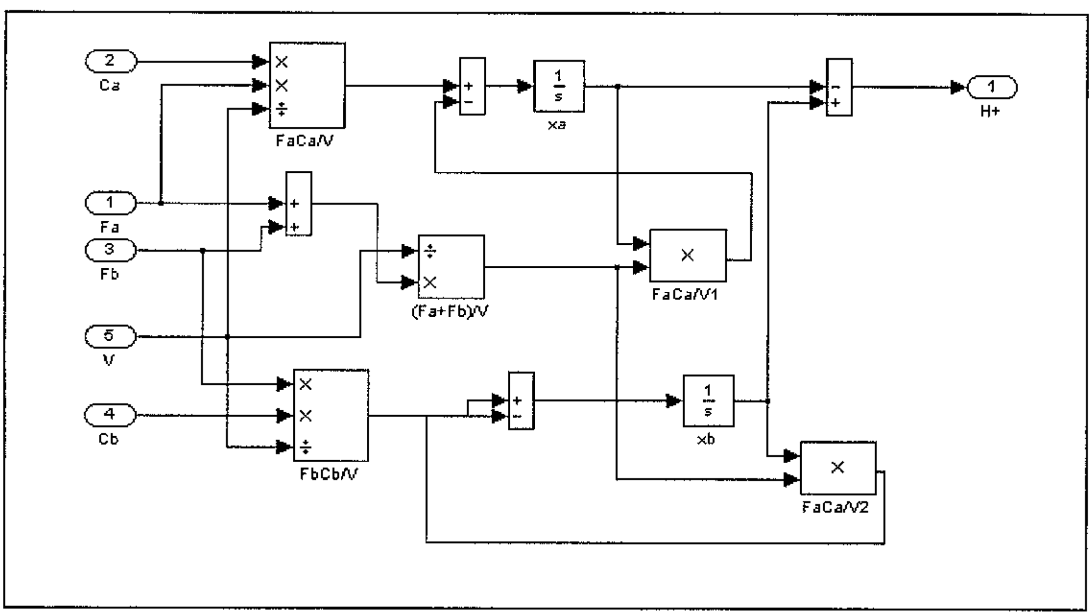

Figure 4.3: pH control plant model.

As an example, the result that obtained from the mathematical model using a sample of the inputs data;

Acid concentration, C_a= 1mol/sec,

Base concentration, C_b= 1.1 mol/sec,

Acid flow, F_a= 3.1 litre/sec,

Base flow, F_b= 3.2 litre/sec,

Volume of CSTR, V=10 litre,

is very promising, as shown in **Figure 4.4**. This mathematical modelling is able to achieve an SASB reaction curve. With this input sample, the acidic value ranges around the lowest pH values (about ≤ pH2) and rises up to higher pH value (≥pH12).

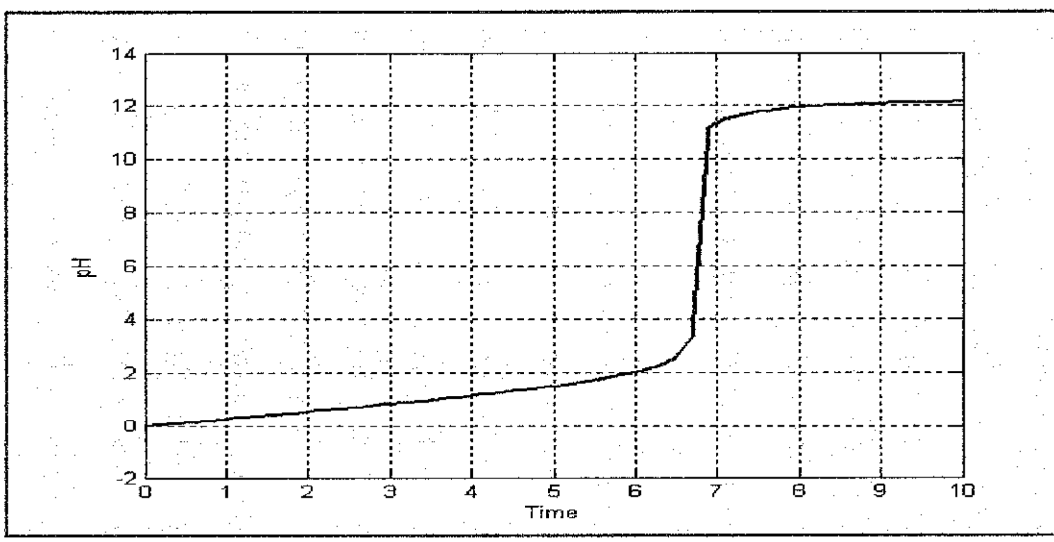

Figure 4.4: Mathematical model simulation for a sample of inputs data

In order to study the relationship between all inputs and output of pH value, a randomized step inputs are used and the result is analysed. **Figure 4.5** shows the mathematical model with random inputs and **Figure 4.6** shows the output for the model.

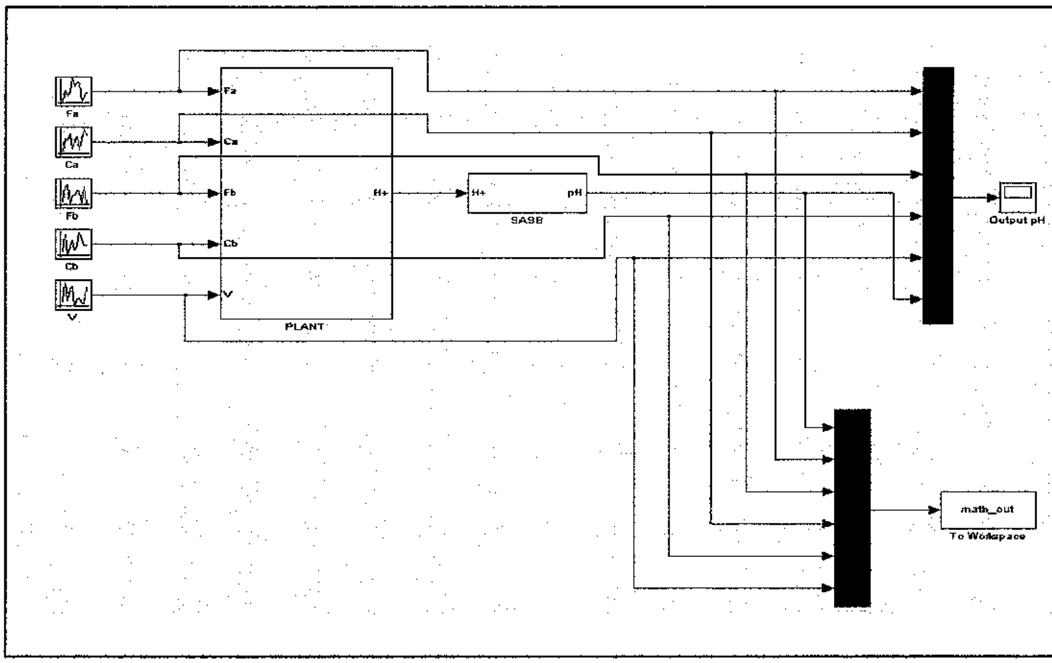

Figure 4.5: Mathematical model simulation block diagram for random step changes

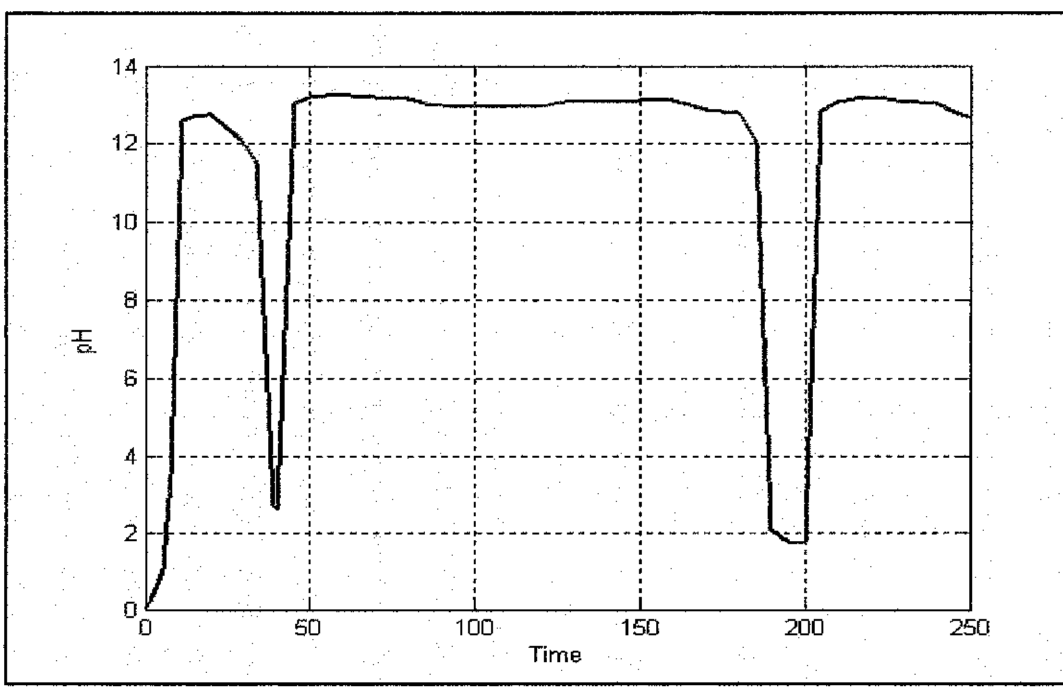

Figure 4.6: Output of SASB reaction curve for random inputs

The random step changes shows that this mathematical modelling fulfilled the strong acid strong base (SASB) reaction curve characteristic since it alternates within the range of the highest pH value to the lowest pH value.

The amount of flow and concentration of acid and base are primary elements that will produce the desired strong acid and strong base reaction curve. In order to obtain the positive gradient reaction curve of titrating acid with base, the amount of flow of alkaline is important. The flow of acid is kept constant at 3.1mol/sec, which in this case, the flow of the acid is set to AUTO mode during the experiment. Looking at **Figure 4.7,** as flow and concentration of alkaline decreases, pH value at the output of the system also decreases and vice versa. Therefore, this mathematical model can be accepted for a pH control of an SASB plant model.

However, the mathematical approach has its limitations, generally resulting from the complexity of mathematical models. Thus, modeling processes to be as realistic as possible, requires a large engineering effort to formulate the equations, determine all the parameter values and solve the equations, usually obtained through numerical methods. Thus, an alternative and simpler modeling method, termed as empirical modeling, has been specifically designed for plant process control.

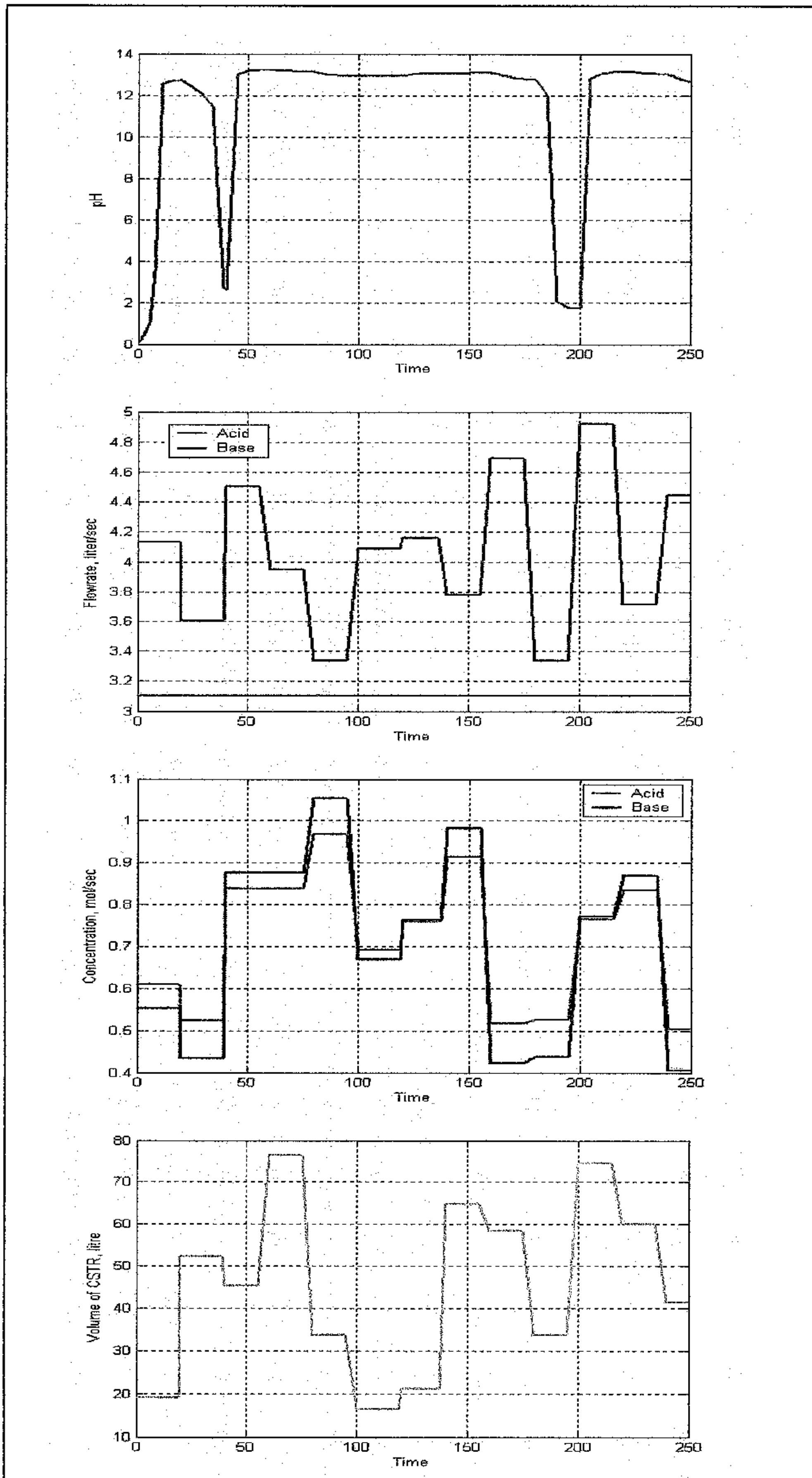

Figure 4.7: Comparison of input data (concentration, flow & volume) to output pH value

4.3 Empirical Modelling

The empirical model pH neutralization is developed based on the process reaction curve where the pH control transfer function is estimated to be a first-order-plus-dead-time model.

The Empirical modelling for all datasets in this project is evaluated by using Method II (refer to **Figure 3.4b**, pg.21). A step change of 1% valve opening is applied to the system and the process reaction curve is observed.

4.3.1 1st Data Set:

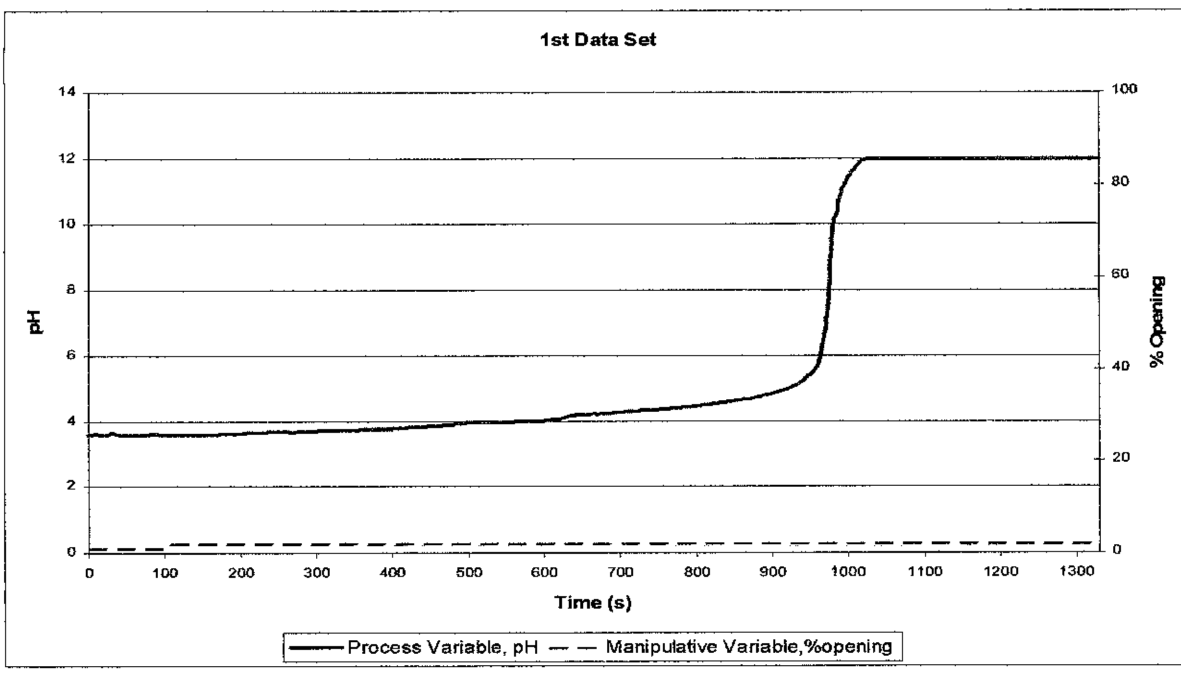

Figure 4.8: Process Reaction Curve 1st Data Set

- Method II calculation:

$$\delta = 1\% opening$$
$$\Delta = 8.42$$
$$K_p = \Delta/\delta = 8.42$$
$$t_{\Delta 63\%} = 872.61s$$
$$t_{\Delta 28\%} = 857.86s$$
$$\tau = 1.5(t_{\Delta 63\%} - t_{\Delta 28\%}) = 22.13s$$
$$\theta = t_{\Delta 63\%} - \tau = 850.48s$$

ThereforeTransferFunction,

$$\boxed{G(s) = \frac{K_p e^{-\theta s}}{\tau s + 1} = \frac{8.42\ e^{-850.48s}}{22.13s + 1}}$$

4.3.2 2nd Data Set:

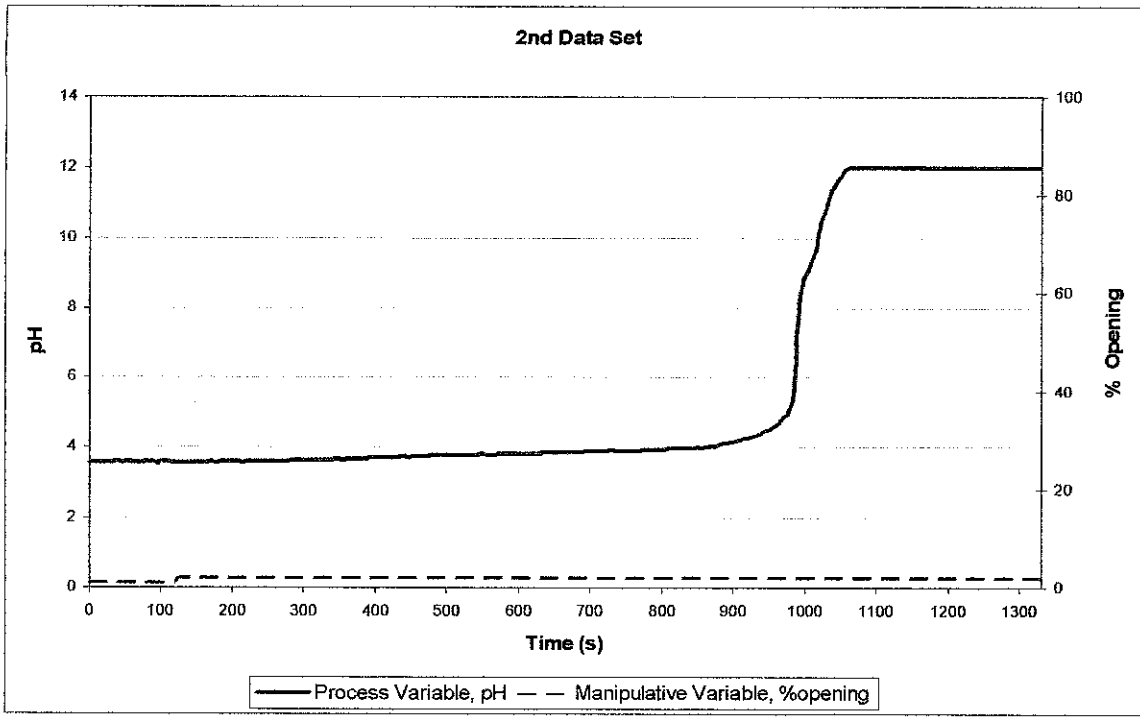

Figure 4.9: Process Reaction Curve for 2nd data set

- Method II calculation:

$$\delta = 1\%opening$$
$$\Delta = 8.43$$
$$K_p = \Delta/\delta = 8.43$$
$$t_{\Delta 63\%} = 874.03s$$
$$t_{\Delta 28\%} = 859.07s$$
$$\tau = 1.5(t_{\Delta 63\%} - t_{\Delta 28\%}) = 22.44s$$
$$\theta = t_{\Delta 63\%} - \tau = 851.59s$$

ThereforeTransferFunction,

$$\boxed{G(s) = \frac{K_p e^{-\theta s}}{\tau s + 1} = \frac{8.43\ e^{-851.59s}}{22.44s + 1}}$$

4.3.3 3rd Data Set:

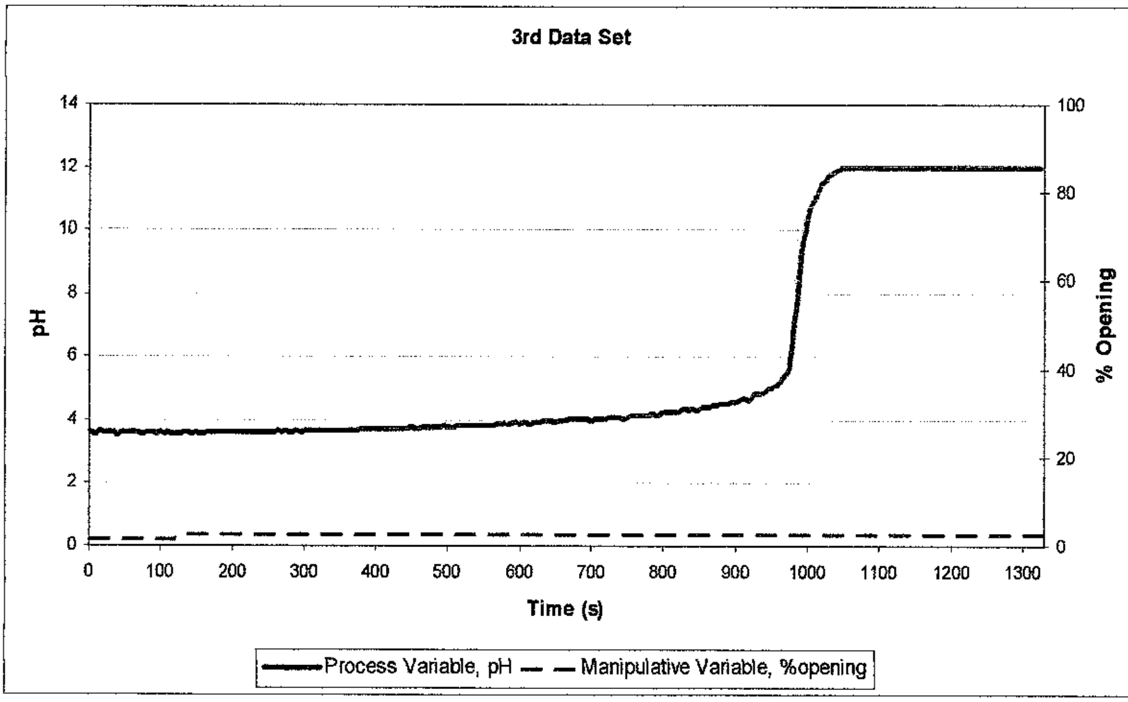

Figure 4.10: Process Reaction Curve for 3rd data set

- Method II calculation:

$$\delta = 1\%opening$$
$$\Delta = 8.43$$
$$K_p = \Delta/\delta = 8.43$$
$$t_{\Delta 63\%} = 870.34s$$
$$t_{\Delta 28\%} = 856.29s$$
$$\tau = 1.5(t_{\Delta 63\%} - t_{\Delta 28\%}) = 21.08s$$
$$\theta = t_{\Delta 63\%} - \tau = 849.29s$$

ThereforeTransferFunction,

$$\boxed{G(s) = \frac{K_p e^{-\theta s}}{\tau s + 1} = \frac{8.43\ e^{-849.29s}}{21.08s + 1}}$$

4.3.4 Comparison

The results developed using empirical modelling of reaction 1st-order-with-dead-time is shown in **Table 4.1**. Method II is more reliable since it considers the time at which the output reaches 28% and 63% of its final value. Therefore, this method is taking more consideration on the rise time of the output which is important for model estimation. Compared to method I, for a highly nonlinear reaction like pH control, it is difficult to estimate for the maximum slope, ΔS, of the curve during the rising transient. Human error on estimating the steepest slope anticipates to failure on developing the most accurate model.

From analysis, the change in ultimate values, time constant, dead time and process gain are approximately the same, for all the three datasets.

Parameters	1st Data	2nd Data	3rd Data
Change in Manipulated Variable, dM	1%	1%	1%
Change in Ultimate Value, dB_u	pH 8.42	pH 8.43	pH 8.43
Apparent Time Constant, T	22.13s	22.44s	21.08s
Apparent Dead Time, T_d	850.48s	851.59s	849.29s
Steady State Process Gain, $K_p = dB_u / dM$	8.42	8.43	8.43

Table 4.1: Parameters comparison table for three datasets

The pH value that can be measured by the transmitter, AT-122, ranges from pH1 to pH14. From plant observation, the process variable for alkaline pH value can goes up to pH13.24. The lowest acidic pH value that can be reached in the CSTR is approximately pH 3.57. The pH output range that can be displayed by the Honeywell Plantscape Software faceplate is from pH2 to pH12, which purposely been set up for an SASB reaction. Nonetheless, for an SASB reaction, the pH values of 12 to 14 are considered as strong alkaline.

Figure 4.11 shows the Simulink block diagram for the three datasets based on results developed for empirical modeling. The simulation output results as expectation where the three outputs is found approximately overlap with each other. The result is shown in **Figure 4.12**.

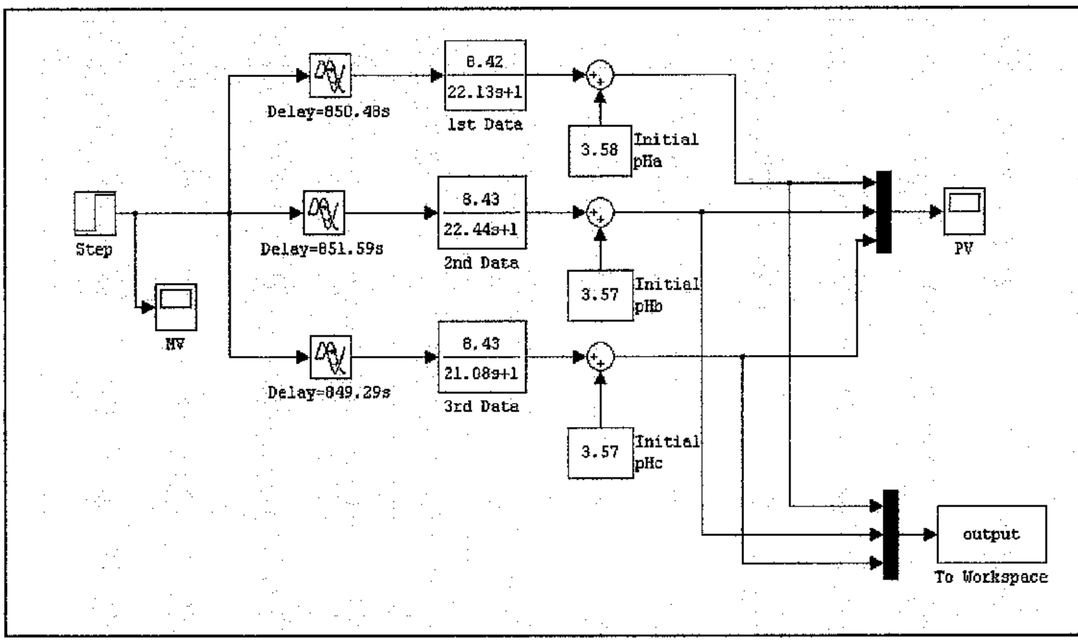

Figure 4.11: Open Loop Control via Simulink

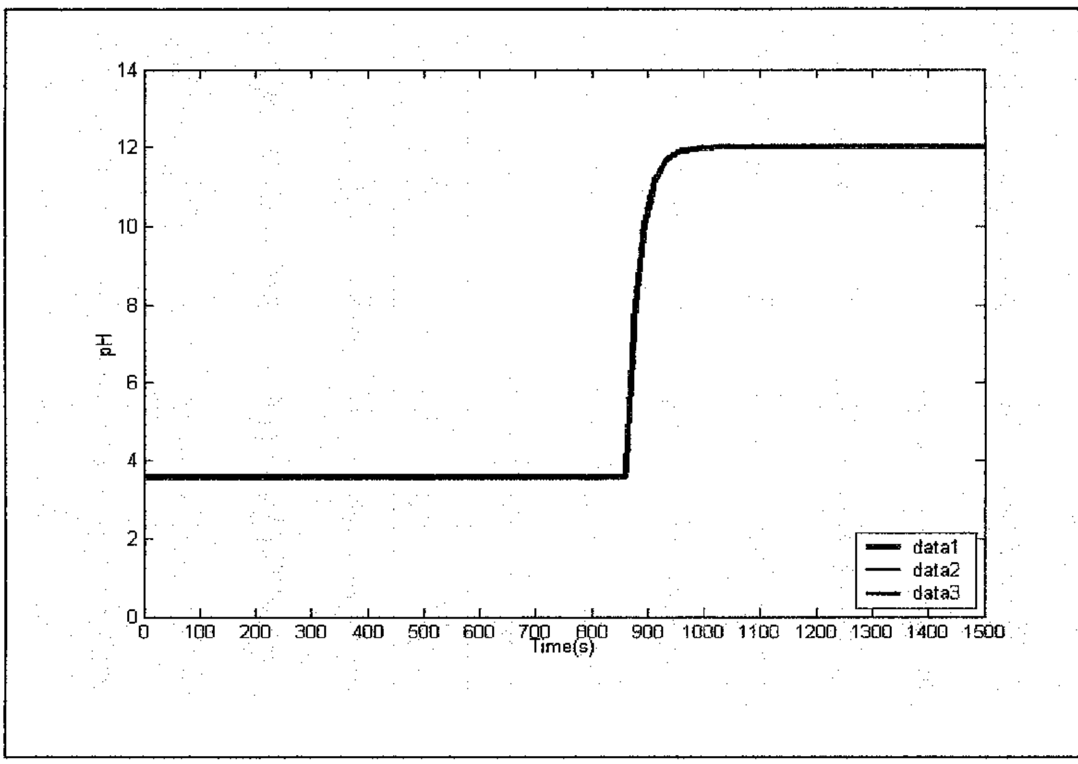

Figure 4.12: Output of empirical modeling using MATLAB-Simulink

The graphical method of empirical modeling has two major limitations; the model obtained is a first-order with dead time transfer function and it requires a sufficiently large step input perturbation to ensure an accurate model. The output responses from empirical model are somewhat inaccurate as compared to the actual output of the plant. Since the pH neutralization model is very nonlinear and is a higher order system, thus this empirical modeling for first order with dead time might not be compatible to the plant. On the other hand, there is another method of empirical modeling which might be relevant for this project which is the Second-Order-Plus-Deadtime (SODT). This method is used to find the second order model parameter of the system proposed by Sudaresan et al. (1978)[9].

In terms of flexibility, modeling a pH neutralization process using the first-order-with-deadtime method is not reliable because the PRC is highly nonlinear and has the tendency to generate large errors during parameters estimation.

4.4 System Identification Toolbox

Statistical Method is implemented by using the System Identification (ARMAX) toolbox. ARMAX stands for Auto Regressive Moving Average with external input model estimator. There are three inputs for the ARMAX blockset; input data, output data and the error data. Data are extracted from Microsoft Excel to the MATLAB workspace.

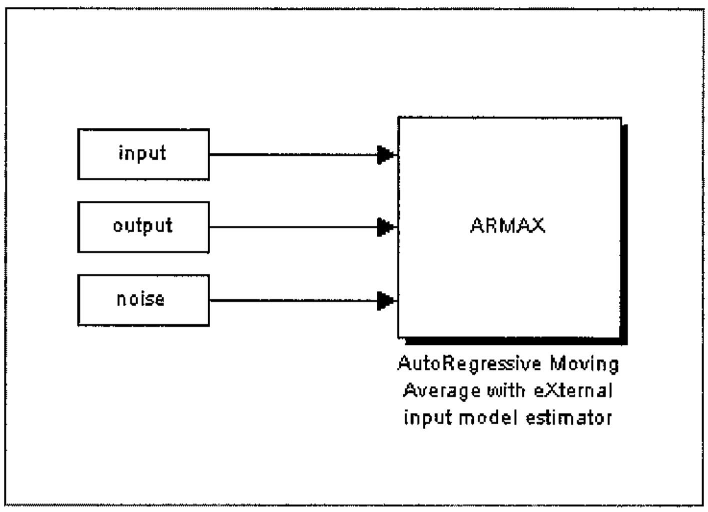

Figure 4.13: ARMAX model simulation

ARMAX system identification computes for the transfer function of the model by learning the data sets of input and output with respect to time. ARMAX will take the mean average value of the data sets and configures the prediction of the transfer function of the model. In this case, the ARMAX blockset is set to a 2^{nd} order system to obtain the most reliable model prediction. Prediction for higher order than 2 resulted in larger error deviations.

Data extracted from the pilot plant will be first validated to identify any outliers or any kind of error that might occur. Any outliers or errors that exist in the dataset will affect the overall results of system identification. The reliability of the dataset is taken into consideration so that the error in the models can be minimized.

Figure 4.14 to **4.16** show the results obtain from the ARMAX simulations. It was found that with a 2^{nd} order function set in the ARMAX blockset, the output will produce an acceptable model prediction. The deviations of error in the predicted models for all three datasets are small.

For a nonlinear process such as pH neutralization, this method can produce a better estimation model than the first-order-with-dead time using empirical modelling technique.

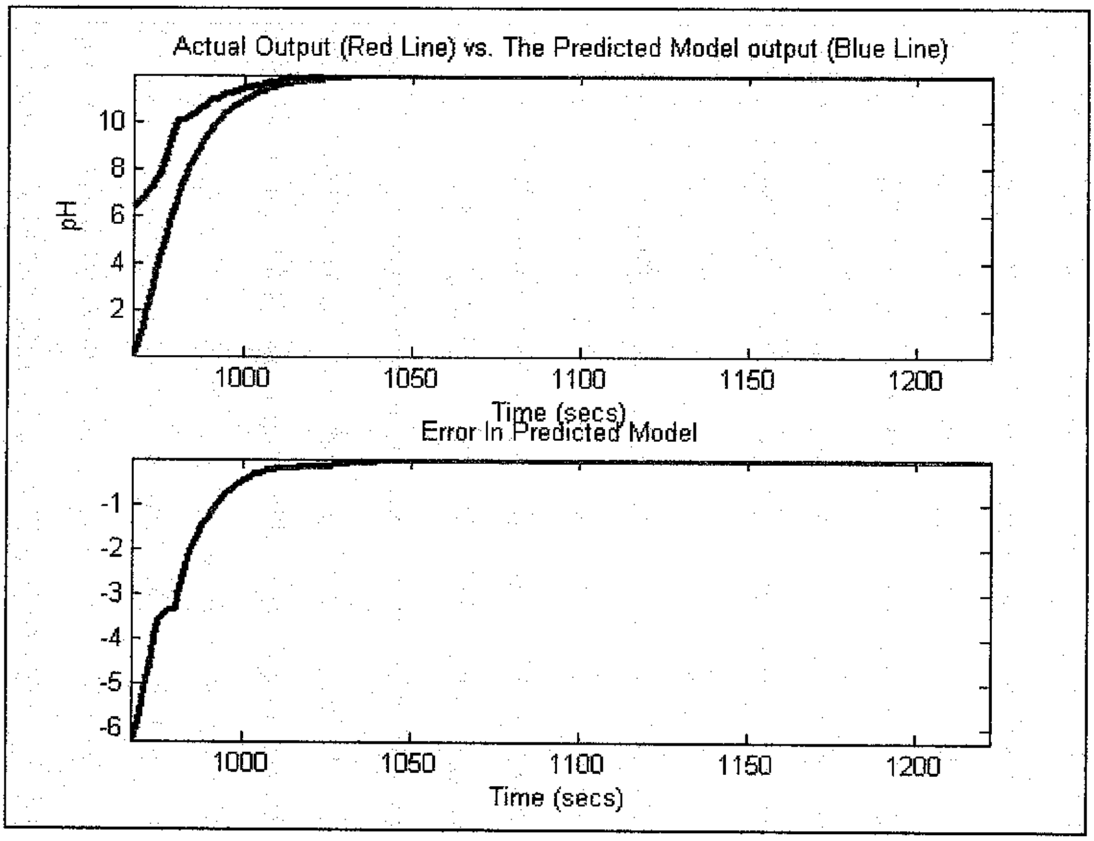

Figure 4.14: ARMAX model prediction for 1st data

From the ARMAX model prediction for 1st data,

Transfer function (continuous):

$$\frac{0.000582\, s^2 - 0.03365\, s + 0.4401}{S^2 + 0.6266\, s + 0.1826}$$

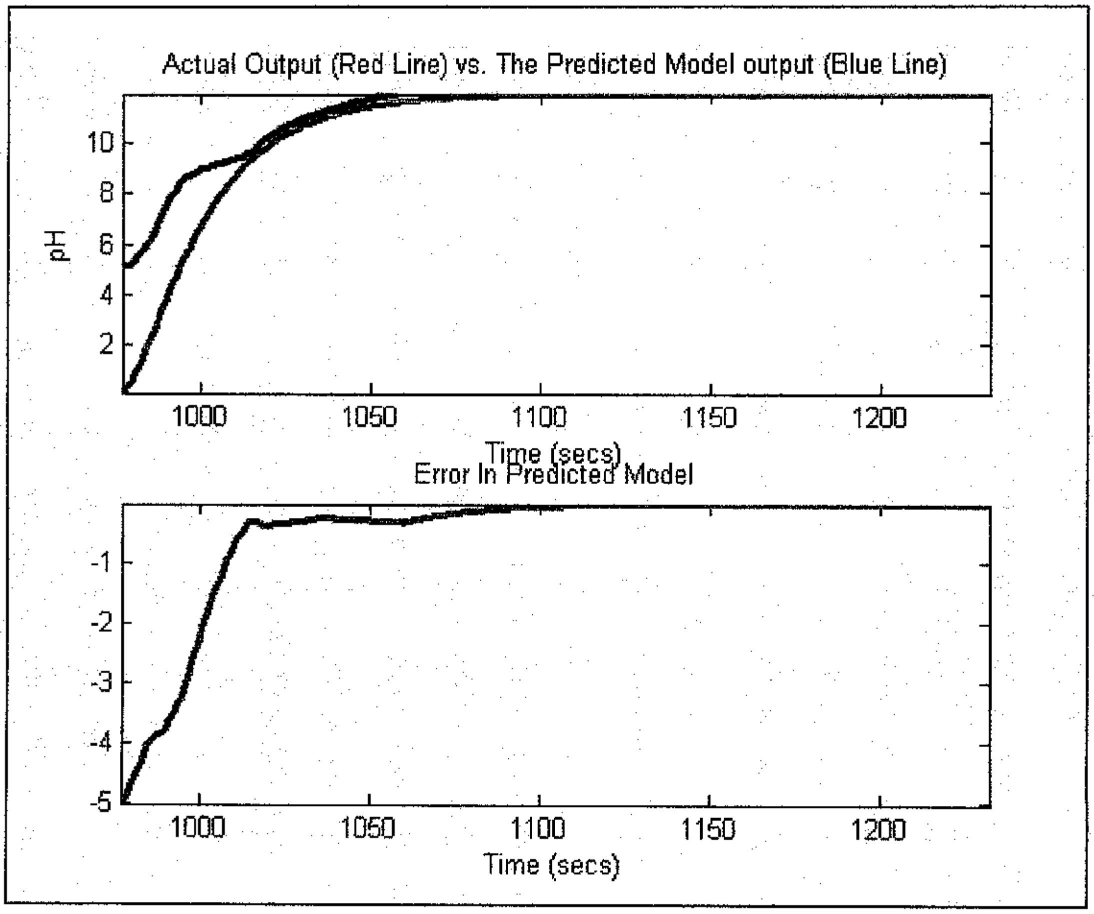

Figure 4.15: ARMAX model prediction for 2nd data

From the ARMAX model prediction for 2nd data,

Transfer function (continuous):

$$\frac{0.0004318\, s^2 + 0.2402\, s + 4.631}{s^2 + 2.103\, s + 0.7716}$$

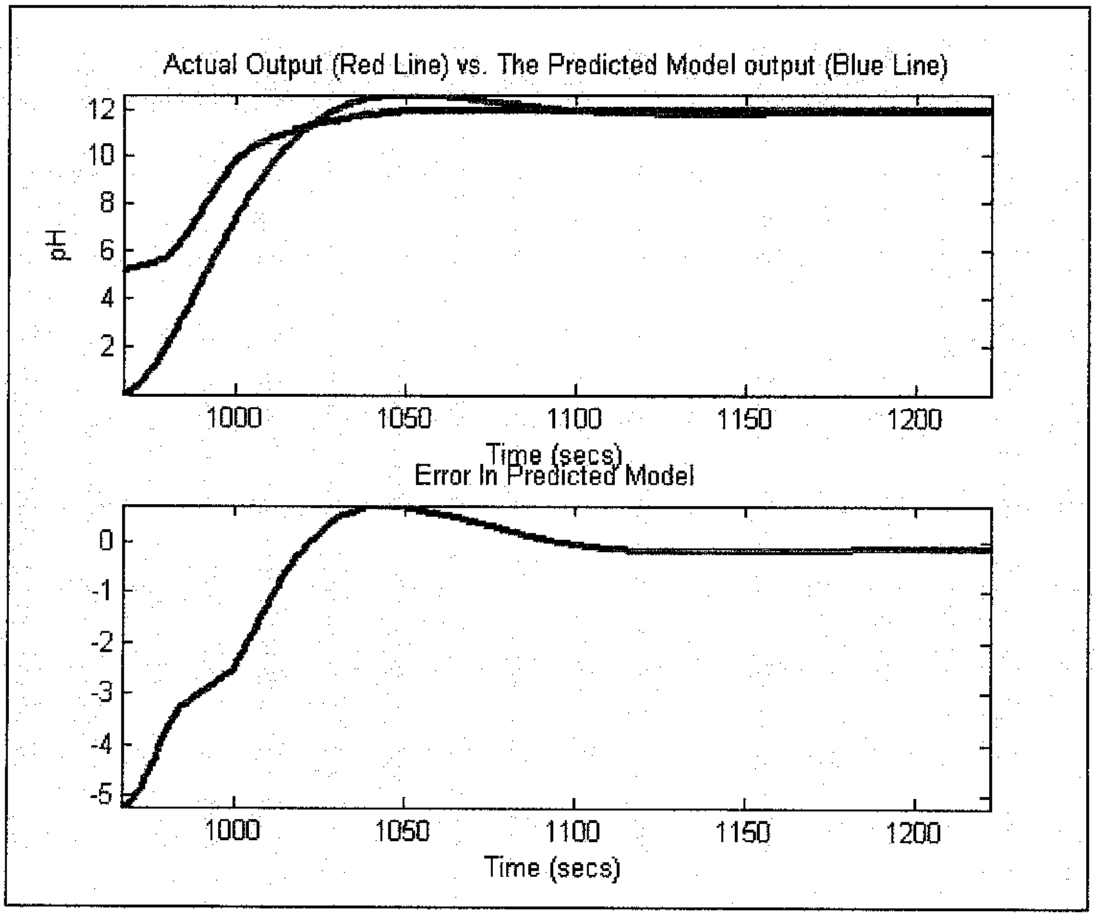

Figure 4.16: ARMAX model prediction for 3rd data

From the ARMAX model prediction for 3rd data,

Transfer function (continuous):

$$\frac{-0.0006461\, s^2 + 0.04426\, s + 1.144}{s^2 + 0.6479\, s + 0.2355}$$

4.5 Neural Network Model

Using neural network, the prediction output is excellent. Referring to **Figure 4.18**, predicted model indicates by the red line overlapped with actual model indicates by the blue line. So far, the result gives the most accurate of model prediction by the implementation of feedforward BP network method.

For this case, in order to get an accurate model prediction, training process has been run for two times. Looking at **Figure 4.17**, for the first training iteration, there is small error deviation between the predicted and actual model. Nonetheless, the predicted model curve obtained from the first iteration can still be considered as good model prediction. Further more, the model prediction can be improved by running second training iteration. The second training iteration works by computing the parameters obtained during the first iteration to the same command functions and develops a new network. The new network is a new model prediction which best fits the actual value. **Figure 4.18** shows how the predicted model fits the actual model. The predicted reaction curve overlaps with the actual reaction curve.

Besides, the method can be employed for any systems since it has various training function methods that can be used according to the systems dynamic. In terms of reliability, it has the ability to construct the model by using the neuron layers. This can be best described by an analogy of a human brain and nerves system where it carries impulses of sensation between the brain and all parts of the human body.

As for this network, there are two layers; the hidden layer and the output layer. The hidden layer has a tangent-sigmoid transfer function which is suitable for learning the nonlinearity of a model, and the output layer utilizes a linear function. These will allow the network to learn both nonlinear and linear relationships between the input and output vectors.

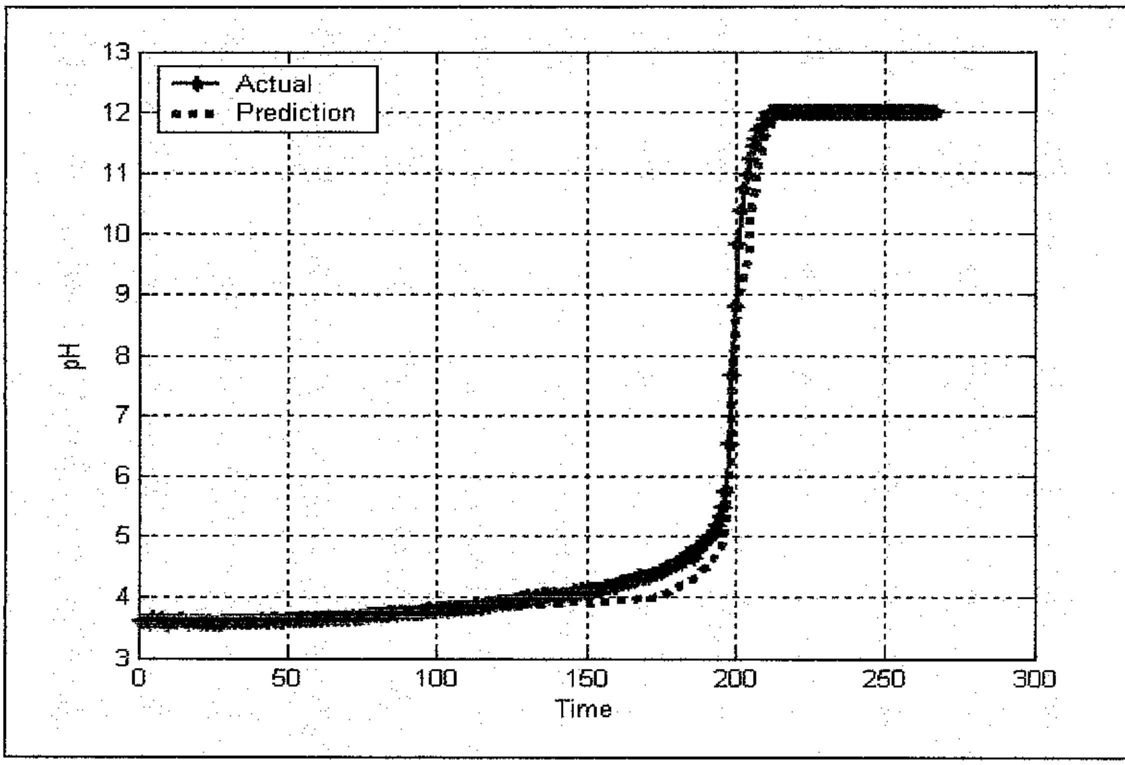

Figure 4.17: Neural network prediction (1st time training)

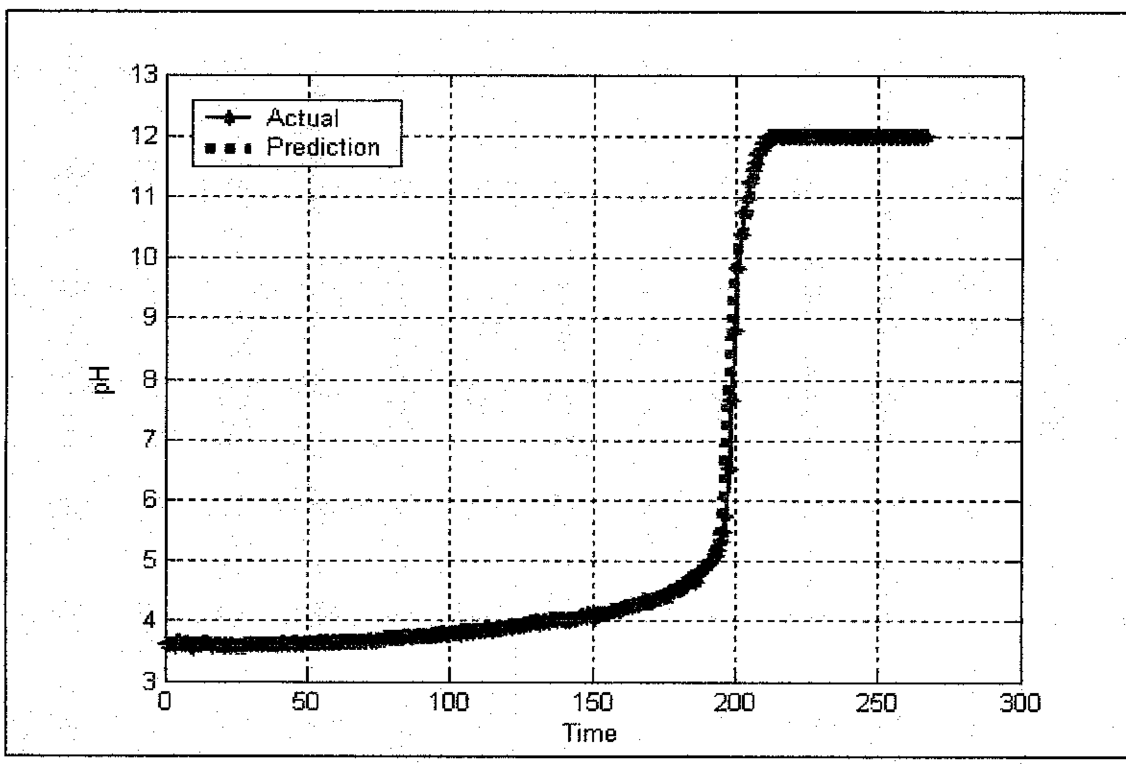

Figure 4.18: Neural network prediction (2nd time training)

However, there are some drawbacks of the application of feedforward BP neural network. Normally, the transfer function of a system is expressed in numerical form, but for neural network, transfer function not able to be analysed. Eventually, neural network represents the system's model in such a way called as 'black box' model, where in this case there are only layers of neuron networks inside the box which yields the model of the system. In addition, since neural network learns from datasets training, thus the datasets must be large enough for a better model prediction.

Note: Refer to **Appendix 1** for the m-file function of feedforward backpropagation neural network.

CHAPTER 5
CONCLUSION AND RECOMMENDATION

5.1 Relevancies to Objectives

For the first objective, the plant experiment had been done on the pH control pilot plant in Instrumentation & Control Laboratory UTP. Many samples of data have been obtained. It was found that the smallest ideal perturbation that can be applied to the pH neutralization control during open loop test is 1% of valve opening. This perturbation is sufficient enough to get the dynamic characteristics of the system.

Then, four modeling approaches are used. Three of the methods are the conventional methods which are mathematical modeling, empirical modeling and statistical modeling. One more method is by using the intelligent approaches which is the neural network. The empirical modeling that is used for this project is based on the methods for first-order-with-dead-time. Whereas, the feedforward backpropagation network method is used for neural modeling.

For the second objective, all modeling is done via MATLAB-Simulink simulation for modeling justification and analysis. A comparative study is conducted to make comparison between conventional and intelligent approach in terms of flexibility, reliability and accuracy. Eventually, from the comparison, it was found that neural network has the ability to model for the best prediction.

5.2 Conclusion

A good model prediction will give good system performance. This is important especially during tuning where systems performance takes place. Inaccurate model will give effects during tuning where it is difficult to tune the output to the desired set point.

Mathematical modelling requires in-depth knowledge of the model and exact values of the parameters in order to get the most accurate and reliable model. This method is also tedious and needs more effort on the mathematical simulation block diagram to get the accurate model simulation. However, the mathematical modelling for the pH neutralization model has the capability to give an accurate result to the actual model provided that knowledge and parameter values are available at hand.

The result obtain from empirical modelling is quite acceptable to the actual reaction curve that is obtain from plant experiment. This model needs further model diagnosis in order to get an optimized model. Different methods can be used during parameters calculation. Method I typically has the tendency to anticipate for larger errors in the parameter estimation; thus, Method II is preferable. However, for a highly nonlinear model like pH neutralization, empirical modeling which utilizes the first-order-with-dead-time is not compatible. The model developed by such calculation is rather a first order reaction curve than a higher reaction order for the real-time data collected from plant experiment.

The system identification toolbox method provided in MATLAB has the ability to estimate the process transfer function based on input and output data fed into its system. It also can give higher order transfer function that closely resembles the actual plant transfer function. Eventhough ARMAX blockset is automatic system identification, it is somewhat difficult to control the simulation range in order to make it compatible to the real-time data range. Since statistical model considered as a computerized modeling, thus it requires good computer configuration basic in order to achieve the desired output.

The result obtained form Neural Network is excellent. The predicted reaction curve is very much similar to the actual reaction curve from plant experiment real-time data. On top of that, in term of accuracy, the model developed by neural network is much more accurate than those obtained from existing conventional methods. Therefore, the MATLAB simulation proves that neural network method for system identification can be trusted for further implementation; for example the hardware implementation. The transfer function not able to be analysed, but nevertheless, this model still working well with the layers of neurons network represented the systems.

5.3 Project Recommendations

5.3.1 Data Gathering

A good selection of data is important so that it is reliable to be used for system identification. This will produce a reliable model that can be trusted. The experiments on the pilot plant should be conducted several times to ensure that data acquired is much more reliable. This is because, the process might yields different result for each experiment.

5.3.2 Second-Order-plus-Deadtime (SODT)

Empirical modeling can also be improved by conventional methods. The other conventional method that can be used for modeling a nonlinear process is the second-order-plus-deadtime (SODT). This method proposed by Sudaresan et al (1978) and is used to find the second order model parameter of the system which might be compatible.

5.3.3 Fuzzy Implementation

For next project recommendation, it would be beneficial if the intelligent method is broader for more methods and approaches such as modeling using the fuzzy techniques. Thus, comparison can also be made between the two intelligent methods.

5.3.4 Physical Implementation

Since, the intelligent methods do not need a lot of time to focus on analyzing the data, and perhaps give a better production, thus, it would be good if this can be implemented on a real plant operation. The project will be more interesting if hardware implementation can be constructed for the intelligent approaches instead of solely software simulations.

5.3.4 Control Implementation

The steps should go further on controlling part where performance test is implemented to the model using intelligent approaches such as fuzzy and neural network. By this means, the reliability of how modeling production helps to improve systems performance can be observed. Perhaps, it would be more interesting to consider for a system that applies intelligent method for both modeling and controlling.

CHAPTER 6

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Appendix 1

The steps taken and the syntax for neural network is illustrated below as in MATLAB m-file,

```
%Prepare data for network training
[PN,minp,maxp,TN,mint,maxt]=premnmx(input,target);

%Create backpropagation network
net=newff(minmax(PN),[1 267],{'tansig','purelin'},'trainlm');
net.trainParam.epochs=6;
net.trainParam.show=1;

%Train the neural network
[net,tr]=train(net, PN, TN);

%Prepare data for testing the network
PN_Test=tramnmx(test_Ip,minp,maxp);

%Testing the network
TN_Test=sim(net,PN_Test);

%Convert the testing output into prediction values for comparison
[queryInputs
predictOutputs]=postmnmx(PN_Test,minp,maxp,TN_Test,mint,maxt);

%Plot the test data and Predict Output for Comparison
plot(test_tgt,'-*'),hold on
plot(predictOutputs,'r:');
```

EXPERIMENT 4:

PH CONTROL IN A CSTR

4.1 OBJECTIVE OF THE EXPERIMENT

(i) To study the pH control pilot plant and prepare a P & I diagram.

(ii) To tune a liquid flow control loop by ultimate gain method.

(iii) To tune a pH control loop by the process reaction curve method.

(iv) To study the closed loop characteristic of the pH control loop of the CSTR.

4.2 INTRODUCTION AND THEORY

pH is defined as $\log_{10}H^+$ and is a measure of the acidity or alkalinity of a liquid. The pH scale is from 1 to 14. with 7 as the pH of neutral water. A value of the pH lower than 7 designate as acidic solution. pH control is important for many chemical processing applications and in pollution control.

In the present experiment the acid flow is under PID flow control while the CSTR pH is controlled by a PID loop controlling the alkaline flow. The loop will be tuned by the ultimate gain method (refer Experiment 3, Table 3.1). The pH control loop will be tuned by the process reaction curve method. (refer to Experiment 2, Table 2.1)

4.3 EXPERIMENTAL EQUIPMENT

The schematic diagram of the experiment set-up is shown in the figure 4.1. Acid solution pumped from tank VE100 by pump P100 into CSTR VE120. The alkaline solution from tank VE110 is pumped by pump P110 into the same CSTR, VE120. The CSTR is equipped with a stirrer and pH transmitter AT122. If desired further neutralisation may be carried out in a second CSTR VE130, or the final neutralisation tank VE140. Besides pH dissolve oxygen can also be measured in a tank VE140.

The major control hardware includes the following:

Flow transmitter	FT120, FT121, FT130
Conductivity transmitter	CT110, CT100
pH transmitter	AT122, AT130, AT140
Dissolved oxygen transmitter	AT141

Flow controller	FIC120, FIC121
pH controller	AIC122, AIC 130
Control valves	FCV120, FCV121, FCV130

The simplified diagram for the flow control and pH control are shown in Figures 4.2 and 4.3 respectively.

4.4 PROCEDURE

The experiment has the following three part:

(i) Tuning flow loop in the acid flow path.
(ii) Tuning pH control loop.
(iii) Operating closed loop pH control.

4.4.1 Start-up

1 Switch on power to the Local Control Panel.
2 Turn the selector to DCS to run the experiment under DCS control. Set it to local if the experiment to be run under local control by using the multi loop controller only.
3 Switch on the main air supply compressor at the compressor room. Wait for the compressor to stop before starting any experiment. This is to ensure that the main instrument air supply to the system is sufficient before running any experiment.
4 Switch on the DCS server and clients. The entire system to start-up automatically. When prompted, key in your user name and password to log in. Consult the supervisor for the correct user name and password.

4.4.2 Preparation of Acidic process stream

1 Fill the acid storage tank with water (up to ½ tank).
2 Use the manual pump provided for acid to pump about 10% of the acid solution into the storage acid tank. Caution: Always add acid to water. Do no add water to the acid.
3 Stir the final solution to ensure homogeneity.

4.4.3 Preparation of Alkaline process stream

1 Fill the alkaline storage tank with water. (up to ½ tank).
2 Use the manual pump provided for alkaline to pump about 30% of the acid solution into the storage acid tank. Caution: Always add alkaline to water.
3 Stir the final solution to ensure homogeneity.

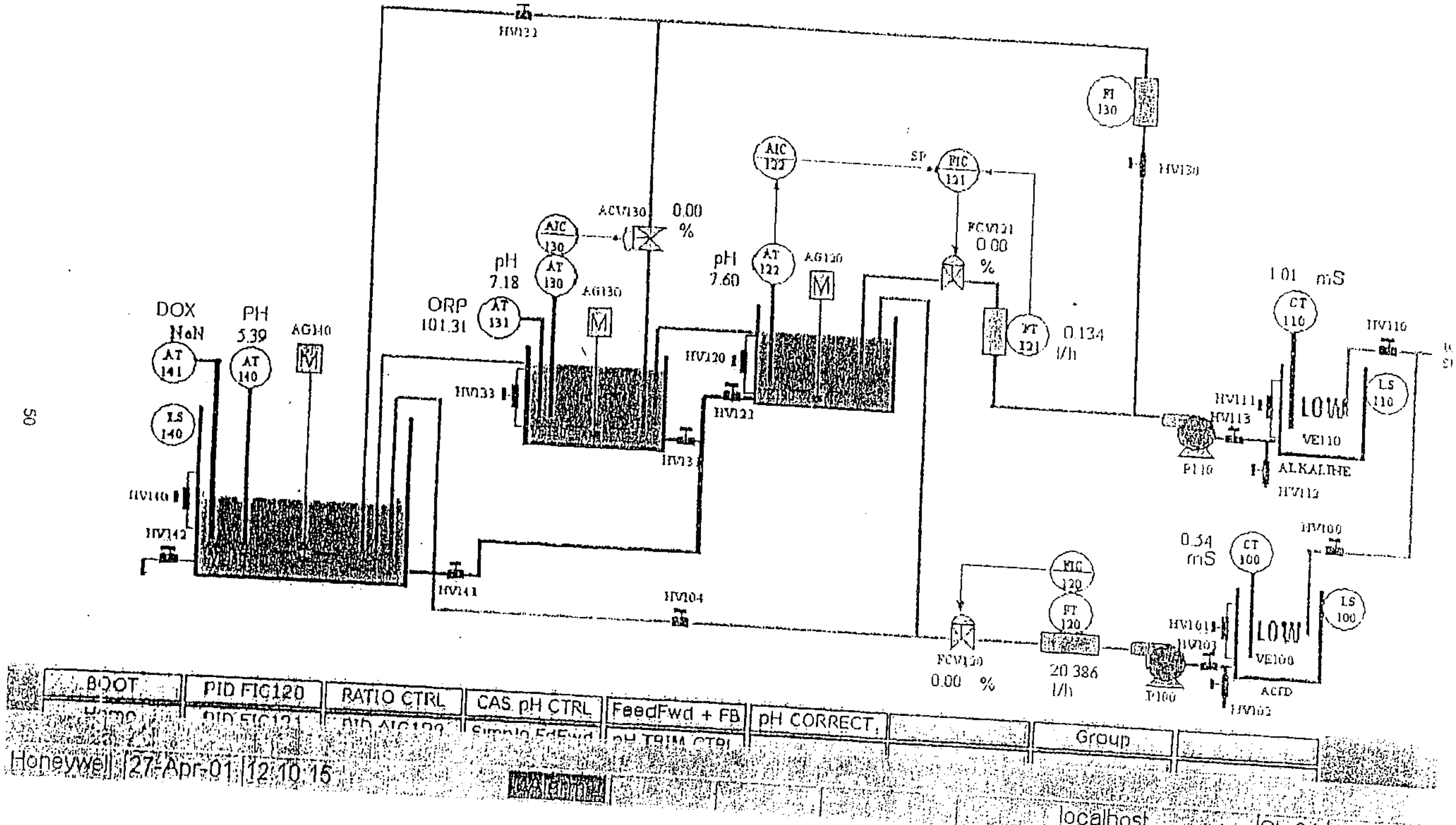

Figure 4.1: CSTR pH control

4.4.4 Start Up

Table 4.4: Preparation and Start-Up

STEP	ACTION	REMARKS
1	Ensure that all Utility Services are ready (i.e. Switch on Power Supply to Control Panel and Switch on Air Supply Systems to the Pilot Plant.	
2	At the Local Control Panel, turn the selector switch to 'DCS'.	
3	Fill the vessel VE100 with water until it is about half full.	
4	Ensure that the DCS is ready (i.e. It is communicating properly with the control panel).	
5	At the computer and the 'Chemical Processing Over-View' display, click on the button [PID FIC 120].	Display for 'Experiment 1 – Simple PID flow Control (FIC 120)' will appear.
6	From the WS/PNL select combo-box, choose DCS. This will transfer control of the pilot plant to the DCS.	Click on drop down box and select 'DCS'.
7	From the Control select combo box, choose FIC120.	
8	At the Controller Faceplate (FIC120) set the controller to MANUAL mode.	Click on drop down box and select 'MANUAL'.
9	Close the control valve FCV120 manually (0%) i.e. a) Setting Control Mode to 'MANUAL', then b) At the MV data entry field, key in 0 and press [Enter].	Same operation to Open/Close other control valve manually.
10	Adjust the Hand Valves at the Pilot Plant as follows: Open Hand Valve HV103 Close Hand Valve HV102	Hand valves to be Open/Closed Fully.

Gain, K_c				
Integral Time, T_I (minute/repeat)				
Derivative Time, T_D (minute/repeat)				

4.4.6 pH Control

Table 4.7: Preparation for pH Control

STEP	ACTION	REMARKS
1	Ensure that all Utility Services are ready (i.e. Switch on Power Supply to Control Panel and Switch on Air Supply Systems to the Pilot Plant.	
2	Adjust the Hand Valves at the Pilot Plant as follows: Open Hand Valve HV103 Close Hand Valve HV102 Close Hand Valve HV112 Open Hand Valve HV113	Hand valves to be Open/Closed Fully.
3	At the Local Control Panel, turn the selector switch to 'DCS'.	
4	Ensure that the DCS is ready (i.e. It is communicating properly with the control panel).	
5	At the computer and the 'Chemical Processing Over-View' display, click on the button [PID AIC 122].	Display for 'Experiment 4– Simple PID pH Control (AIC 122)' will appear.
6	From the WS/PNL select combo-box, choose DCS. This will transfer control of the pilot plant to the DCS.	Click on drop down box and select 'DCS'.
7	From the Control select combo box, choose pH AIC122	
8	At the FIC120 Controller Faceplate: - Set the controller to AUTO mode. - Set its output to 100% (fully open). - Set its P, I and D values obtained from Experiment 1.	Set MV = 100, K_p, I and D accordingly.

9	Open HV100 and HV110 to fill vessels VE100 and VE110 with water until each of them is about ¼ full.	
10	Close HV110 when the water level at VE110 is ¼ full.	
11	When the water level at VE100 is about ¼ full, start pump P100 via DCS to fill the reaction vessel VE120. Continue to fill VE100.	
12	When the water level at the reaction vessel VE120 is above its agitator blades stop pump P100.	
13	Close HV 100 when the water level at VE100 is ¼ full.	
14	At the vessel VE100 use the hand pump provided to add concentrated sulphuric acid into it [Note: do not add water into concentrated acid instead add acid to water]. Observe the reading of the conductivity meter. Stop adding acid when the conductivity of the solution is approximately 100 micron-Siemen.	The students are advised to wear eye protection goggle and rubber gloves when dealing with acid solution.
15	At the vessel VE110 use the hand pump provided to add concentrated caustic soda (Sodium hydroxide) solution into it. Observe the reading of the conductivity meter. Stop adding acid when the conductivity of the solution is approximately 100 micron-Siemen.	The students are advised to wear eye protection goggle and rubber gloves when dealing with acid solution.
16	At the AIC122 Controller Faceplate, set the controller to MANUAL mode.	Click on drop down box and select 'MANUAL'.
17	Close the Control Valve pHCV12 manually (0% open).	pHCV12 is the same Control Valve as FCV121.
18	Ensure that all tanks are properly covered.	

Table 4.8: Start-Up

STEP	ACTION	REMARKS
1	Start agitator AG120 via DCS.	

2	At the FIC120 Controller Faceplate: - Adjust the Controller Set Point to 0.05 m^3/h	Set SP = 50
3	Start pump P100 via DCS.	

4.4.7 Identification of pH Process

Table 4.9: Process Identification for pH Control Loop

STEP	ACTION	REMARKS
1	At the AIC 122 Controller Faceplate, manually Open Control Valve pHCV122 to 10%.	Set MV = 10.
2	Start pump P110 via the computer.	Click on drop down box and select 'ON'.
3	Observe the pH curve from the Trend Window and wait until it has stabilised.	
4	Adjust the output of controller AIC122 to obtain a stable pH value (AT122) between 6.5 and 7.5.	Set SP = 7.
5	At the Controller Faceplate (AIC122) make a Step change of between 10 to 20% to the control valve FCV121 manually.	Set SP = 7.7. Adjust controller MV.
6	Observe the pH curve (AT122) from the Trend Window and wait until it has stabilised to a new constant value and freeze the trend window.	This is the process Reaction curve.
7	Print out the pH trend curve.	Print in colour.
8	Stop both the pumps P100 and P101, and the agitator AG120 via DCS. Then set the controllers FIC120 and FIC121 to MANUAL mode.	

Table 4.10: Result Analysis for pH Control Loop

STEP	ACTION	REMARKS
9	Compare the process value curve with a set of expected process Reaction Curve provided in Figure 2.6.	
10	Identify the process response with the corresponding Reaction Curve.	
11	Make several measurements as per the Reaction Curve chart.	Refer to Table 4.11.
12	Sketch a Block Diagram to represent the process and describe the characteristic of this process.	Dead time, Capacity/Rate of Rise, Time Constant, Noise.
13	Using the printed graph obtained from section above (process analysis) above, measure and tabulate the relevant values as required. Refer table 4.9.	Note: dB_u and dM are changes from the 1st stable output to the 2nd.
14	Based on the equations for Open Loop Tuning, calculate the required controller tuning parameters. Refer table 2.1.	
15	At the AIC122 controller faceplate. Key in the calculated controller tuning parameters.	

Table 4.11: CSTR Model

Type of model	Time constant, T_1	Time constant, T_2	Decay time, τ
First Order			
First Order with decay time			
Second order			
Second order with decay time			

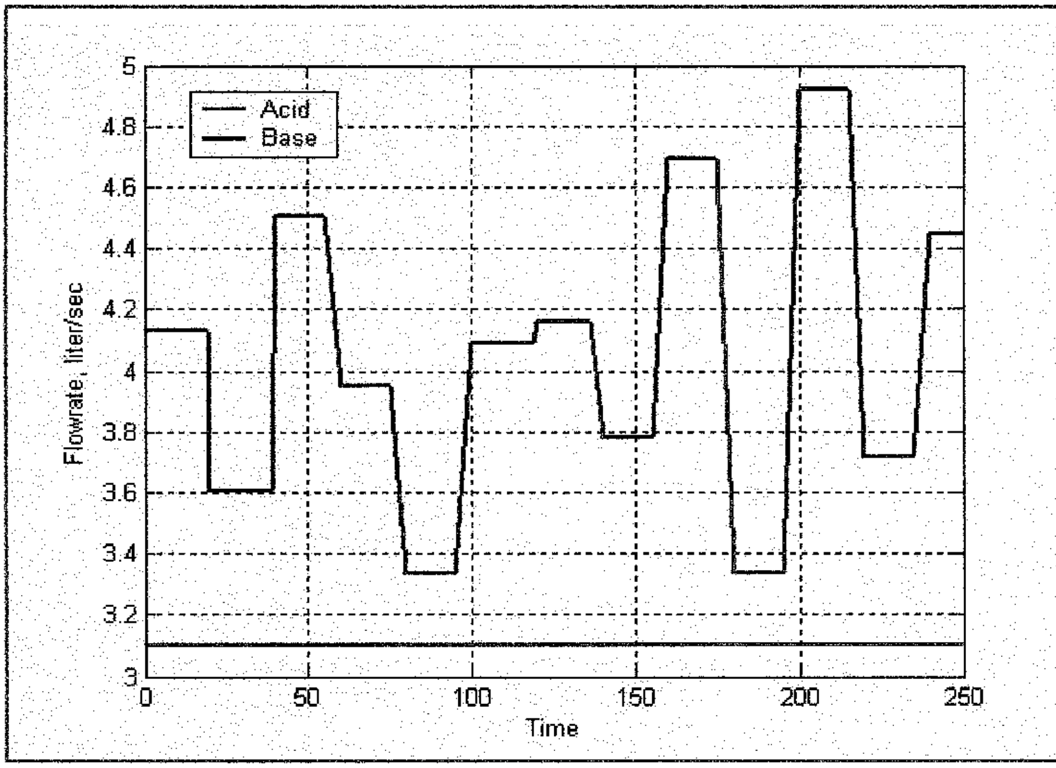

Figure i: Variable Flowrate of Acid & Base for random step changes.

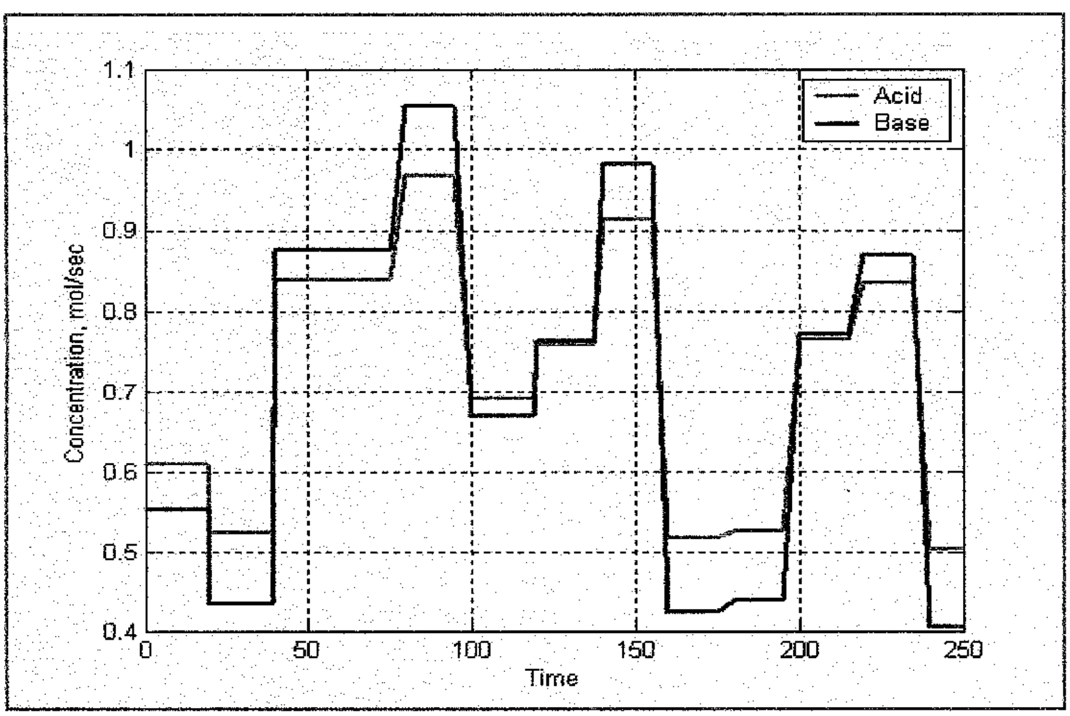

Figure ii: Variable Concentration of Acid & Base for random step changes

Appendix 3

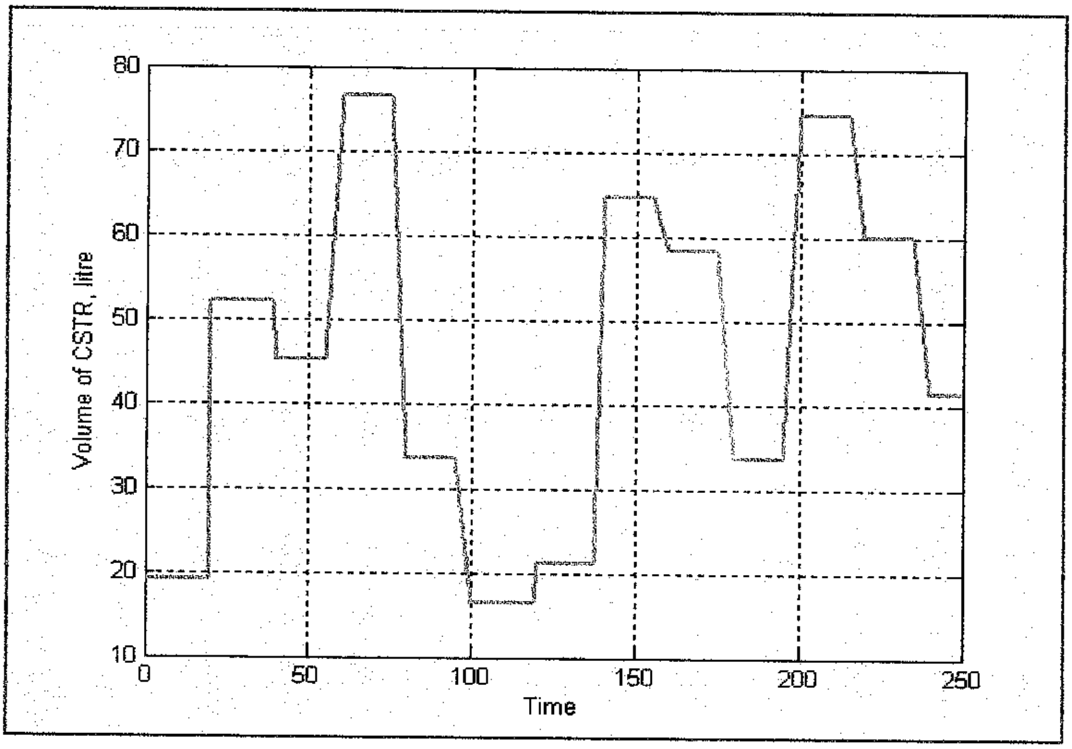

Figure iii: Volume of CSTR for random step inputs

1st Real-time Data

Time (s)	PV	MV
0	3.61	1.5
5	3.61	1.5
10	3.61	1.5
15	3.57	1.5
20	3.66	1.5
25	3.6	1.5
30	3.61	1.5
35	3.63	1.5
40	3.6	1.5
45	3.53	1.5
50	3.6	1.5
55	3.6	1.5
60	3.61	1.5
65	3.62	1.5
70	3.63	1.5
75	3.61	1.5
80	3.57	1.5
85	3.6	1.5
90	3.61	1.5
95	3.6	1.5
100	3.56	1.5
105	3.61	1.5
110	3.58	1.5
115	3.61	1.5
120	3.57	1.5
125	3.57	2.5
130	3.57	2.5
135	3.58	2.5
140	3.6	2.5
145	3.6	2.5
150	3.59	2.5
155	3.6	2.5
160	3.59	2.5
165	3.59	2.5
170	3.61	2.5
175	3.6	2.5
180	3.6	2.5
185	3.61	2.5
190	3.61	2.5
195	3.6	2.5
200	3.6	2.5
205	3.62	2.5
210	3.6	2.5
215	3.61	2.5
220	3.62	2.5
225	3.61	2.5
230	3.62	2.5
235	3.61	2.5
240	3.61	2.5
245	3.62	2.5
250	3.63	2.5
255	3.62	2.5
260	3.62	2.5
265	3.64	2.5
270	3.65	2.5
275	3.64	2.5
280	3.65	2.5
285	3.64	2.5
290	3.64	2.5
295	3.66	2.5
300	3.64	2.5
305	3.66	2.5
310	3.65	2.5
315	3.66	2.5
320	3.65	2.5
325	3.67	2.5
330	3.66	2.5
335	3.67	2.5
340	3.66	2.5
345	3.67	2.5
350	3.66	2.5
355	3.68	2.5
360	3.67	2.5
365	3.67	2.5
370	3.69	2.5
375	3.69	2.5
380	3.68	2.5
385	3.71	2.5
390	3.71	2.5
395	3.72	2.5
400	3.72	2.5
405	3.72	2.5
410	3.71	2.5
415	3.73	2.5
420	3.74	2.5
425	3.74	2.5
430	3.72	2.5
435	3.74	2.5
440	3.75	2.5
445	3.74	2.5
450	3.75	2.5
455	3.76	2.5
460	3.75	2.5
465	3.74	2.5
470	3.76	2.5
475	3.77	2.5
480	3.77	2.5
485	3.79	2.5
490	3.77	2.5
495	3.78	2.5
500	3.81	2.5
505	3.79	2.5
510	3.8	2.5
515	3.78	2.5
520	3.82	2.5
525	3.81	2.5

Time (s)	PV	MV
530	3.83	2.5
535	3.81	2.5
540	3.82	2.5
545	3.83	2.5
550	3.83	2.5
555	3.82	2.5
560	3.85	2.5
565	3.85	2.5
570	3.84	2.5
575	3.86	2.5
580	3.87	2.5
585	3.87	2.5
590	3.88	2.5
595	3.89	2.5
600	3.92	2.5
605	3.9	2.5
610	3.92	2.5
615	3.92	2.5
620	3.91	2.5
625	3.92	2.5
630	3.96	2.5
635	3.96	2.5
640	3.97	2.5
645	3.97	2.5
650	4	2.5
655	3.96	2.5
660	3.97	2.5
665	4.01	2.5
670	3.97	2.5
675	4.04	2.5
680	4.03	2.5
685	4.02	2.5
690	4.03	2.5
695	4.04	2.5
700	4.02	2.5
705	4	2.5
710	4.05	2.5
715	4.04	2.5
720	4.05	2.5
725	4.07	2.5
730	4.09	2.5
735	4.08	2.5
740	4.12	2.5
745	4.1	2.5
750	4.05	2.5
755	4.12	2.5
760	4.13	2.5
765	4.14	2.5
770	4.13	2.5
775	4.14	2.5
780	4.17	2.5
785	4.17	2.5
790	4.19	2.5
795	4.17	2.5

Time (s)	PV	MV
800	4.21	2.5
805	4.24	2.5
810	4.25	2.5
815	4.24	2.5
820	4.28	2.5
825	4.26	2.5
830	4.31	2.5
835	4.36	2.5
840	4.33	2.5
845	4.34	2.5
850	4.32	2.5
855	4.36	2.5
860	4.4	2.5
865	4.4	2.5
870	4.42	2.5
875	4.46	2.5
880	4.48	2.5
885	4.52	2.5
890	4.52	2.5
895	4.53	2.5
900	4.56	2.5
905	4.57	2.5
910	4.63	2.5
915	4.71	2.5
920	4.71	2.5
925	4.65	2.5
930	4.77	2.5
935	4.82	2.5
940	4.86	2.5
945	4.91	2.5
950	4.98	2.5
955	5.01	2.5
960	5.09	2.5
965	5.17	2.5
970	5.32	2.5
975	5.46	2.5
980	5.72	2.5
985	6.53	2.5
990	7.67	2.5
995	8.81	2.5
1000	9.84	2.5
1005	10.37	2.5
1010	10.74	2.5
1015	10.97	2.5
1020	11.23	2.5
1025	11.45	2.5
1030	11.54	2.5
1035	11.71	2.5
1040	11.77	2.5
1045	11.87	2.5
1050	11.94	2.5
1055	12	2.5
1060	12	2.5
1065	12	2.5

Time (s)	PV	MV
1070	12	2.5
1075	12	2.5
1080	12	2.5
1085	12	2.5
1090	12	2.5
1095	12	2.5
1100	12	2.5
1105	12	2.5
1110	12	2.5
1115	12	2.5
1120	12	2.5
1125	12	2.5
1130	12	2.5
1135	12	2.5
1140	12	2.5
1145	12	2.5
1150	12	2.5
1155	12	2.5
1160	12	2.5
1165	12	2.5
1170	12	2.5
1175	12	2.5
1180	12	2.5
1185	12	2.5
1190	12	2.5
1195	12	2.5
1200	12	2.5
1205	12	2.5
1210	12	2.5
1215	12	2.5
1220	12	2.5
1225	12	2.5
1230	12	2.5
1235	12	2.5
1240	12	2.5
1245	12	2.5
1250	12	2.5
1255	12	2.5
1260	12	2.5
1265	12	2.5
1270	12	2.5
1275	12	2.5
1280	12	2.5
1285	12	2.5
1290	12	2.5
1295	12	2.5
1300	12	2.5
1305	12	2.5
1310	12	2.5
1315	12	2.5
1320	12	2.5
1325	12	2.5
1330	12	2.5

2nd Real-time Data

Time (s)	PV	MV	Time (s)	PV	MV
0	3.57	1	265	3.63	2
5	3.58	1	270	3.63	2
10	3.57	1	275	3.63	2
15	3.57	1	280	3.63	2
20	3.57	1	285	3.65	2
25	3.58	1	290	3.64	2
30	3.59	1	295	3.65	2
35	3.59	1	300	3.64	2
40	3.6	1	305	3.64	2
45	3.59	1	310	3.65	2
50	3.6	1	315	3.65	2
55	3.6	1	320	3.66	2
60	3.58	1	325	3.66	2
65	3.57	1	330	3.67	2
70	3.57	1	335	3.65	2
75	3.57	1	340	3.66	2
80	3.61	1	345	3.68	2
85	3.58	1	350	3.68	2
90	3.61	1	355	3.66	2
95	3.56	1	360	3.68	2
100	3.6	1	365	3.69	2
105	3.61	1	370	3.69	2
110	3.6	1	375	3.69	2
115	3.57	1	380	3.69	2
120	3.58	1	385	3.69	2
125	3.57	2	390	3.7	2
130	3.57	2	395	3.71	2
135	3.57	2	400	3.71	2
140	3.58	2	405	3.71	2
145	3.59	2	410	3.72	2
150	3.58	2	415	3.71	2
155	3.59	2	420	3.73	2
160	3.59	2	425	3.73	2
165	3.58	2	430	3.73	2
170	3.6	2	435	3.74	2
175	3.59	2	440	3.75	2
180	3.59	2	445	3.74	2
185	3.6	2	450	3.75	2
190	3.6	2	455	3.76	2
195	3.6	2	460	3.76	2
200	3.6	2	465	3.75	2
205	3.6	2	470	3.76	2
210	3.6	2	475	3.77	2
215	3.59	2	480	3.78	2
220	3.6	2	485	3.79	2
225	3.61	2	490	3.79	2
230	3.61	2	495	3.8	2
235	3.61	2	500	3.78	2
240	3.61	2	505	3.79	2
245	3.62	2	510	3.79	2
250	3.61	2	515	3.8	2
255	3.62	2	520	3.8	2
260	3.62	2	525	3.8	2

Time (s)	PV	MV
530	3.79	2
535	3.79	2
540	3.8	2
545	3.81	2
550	3.82	2
555	3.81	2
560	3.81	2
565	3.8	2
570	3.81	2
575	3.82	2
580	3.84	2
585	3.83	2
590	3.83	2
595	3.84	2
600	3.83	2
605	3.82	2
610	3.82	2
615	3.83	2
620	3.83	2
625	3.83	2
630	3.84	2
635	3.85	2
640	3.85	2
645	3.85	2
650	3.86	2
655	3.86	2
660	3.86	2
665	3.86	2
670	3.86	2
675	3.86	2
680	3.87	2
685	3.88	2
690	3.88	2
695	3.89	2
700	3.89	2
705	3.91	2
710	3.92	2
715	3.91	2
720	3.91	2
725	3.92	2
730	3.93	2
735	3.92	2
740	3.91	2
745	3.92	2
750	3.92	2
755	3.9	2
760	3.92	2
765	3.92	2
770	3.92	2
775	3.93	2
780	3.93	2
785	3.93	2
790	3.94	2
795	3.95	2
800	3.94	2
805	3.95	2
810	3.96	2
815	3.96	2
820	3.96	2
825	3.96	2
830	3.97	2
835	3.97	2
840	3.97	2
845	3.97	2
850	4	2
855	3.99	2
860	4	2
865	4.02	2
870	4.03	2
875	4.05	2
880	4.07	2
885	4.1	2
890	4.12	2
895	4.14	2
900	4.16	2
905	4.2	2
910	4.21	2
915	4.26	2
920	4.27	2
925	4.31	2
930	4.35	2
935	4.38	2
940	4.45	2
945	4.48	2
950	4.52	2
955	4.59	2
960	4.67	2
965	4.73	2
970	4.86	2
975	4.95	2
980	5.23	2
985	6.09	2
990	7.59	2
995	8.59	2
1000	8.95	2
1005	9.18	2
1010	9.37	2
1015	9.65	2
1020	10.29	2
1025	10.68	2
1030	11.01	2
1035	11.21	2
1040	11.44	2
1045	11.62	2
1050	11.77	2
1055	11.91	2
1060	12	2
1065	12	2

Time (s)	PV	MV
1070	12	2
1075	12	2
1080	12	2
1085	12	2
1090	12	2
1095	12	2
1100	12	2
1105	12	2
1110	12	2
1115	12	2
1120	12	2
1125	12	2
1130	12	2
1135	12	2
1140	12	2
1145	12	2
1150	12	2
1155	12	2
1160	12	2
1165	12	2
1170	12	2
1175	12	2
1180	12	2
1185	12	2
1190	12	2
1195	12	2
1200	12	2
1205	12	2
1210	12	2
1215	12	2
1220	12	2
1225	12	2
1230	12	2
1235	12	2
1240	12	2
1245	12	2
1250	12	2
1255	12	2
1260	12	2
1265	12	2
1270	12	2
1275	12	2
1280	12	2
1285	12	2
1290	12	2
1295	12	2
1300	12	2
1305	12	2
1310	12	2
1315	12	2
1320	12	2
1325	12	2
1330	12	2

3rd Real-time Data

Time (s)	MV	PV	Time (s)	MV	PV
0	1	3.59	265	2	3.68
5	1	3.59	270	2	3.66
10	1	3.6	275	2	3.68
15	1	3.58	280	2	3.69
20	1	3.57	285	2	3.69
25	1	3.59	290	2	3.69
30	1	3.63	295	2	3.69
35	1	3.6	300	2	3.69
40	1	3.58	305	2	3.7
45	1	3.58	310	2	3.71
50	1	3.58	315	2	3.71
55	1	3.58	320	2	3.71
60	1	3.59	325	2	3.72
65	1	3.59	330	2	3.71
70	1	3.59	335	2	3.71
75	1	3.59	340	2	3.71
80	1	3.59	345	2	3.71
85	1	3.6	350	2	3.72
90	1	3.6	355	2	3.71
95	1	3.58	360	2	3.73
100	1	3.57	365	2	3.73
105	2	3.58	370	2	3.73
110	2	3.58	375	2	3.74
115	2	3.58	380	2	3.75
120	2	3.58	385	2	3.74
125	2	3.58	390	2	3.75
130	2	3.58	395	2	3.76
135	2	3.58	400	2	3.76
140	2	3.58	405	2	3.77
145	2	3.58	410	2	3.78
150	2	3.59	415	2	3.79
155	2	3.59	420	2	3.79
160	2	3.59	425	2	3.8
165	2	3.59	430	2	3.81
170	2	3.59	435	2	3.81
175	2	3.6	440	2	3.83
180	2	3.6	445	2	3.83
185	2	3.61	450	2	3.84
190	2	3.61	455	2	3.85
195	2	3.61	460	2	3.86
200	2	3.62	465	2	3.86
205	2	3.62	470	2	3.88
210	2	3.63	475	2	3.89
215	2	3.63	480	2	3.89
220	2	3.64	485	2	3.91
225	2	3.65	490	2	3.92
230	2	3.66	495	2	3.93
235	2	3.66	500	2	3.95
240	2	3.67	505	2	3.95
245	2	3.67	510	2	3.95
250	2	3.68	515	2	3.95
255	2	3.68	520	2	3.95
260	2	3.68	525	2	3.96

Time (s)	MV	PV	Time (s)	MV	PV
530	2	3.96	800	2	4.45
535	2	3.96	805	2	4.47
540	2	3.96	810	2	4.49
545	2	3.96	815	2	4.51
550	2	3.96	820	2	4.51
555	2	3.96	825	2	4.52
560	2	3.96	830	2	4.54
565	2	3.97	835	2	4.55
570	2	3.97	840	2	4.57
575	2	3.97	845	2	4.59
580	2	3.97	850	2	4.6
585	2	3.97	855	2	4.62
590	2	4	860	2	4.64
595	2	3.99	865	2	4.66
600	2	4	870	2	4.68
605	2	4.02	875	2	4.7
610	2	4.03	880	2	4.72
615	2	4.05	885	2	4.74
620	2	4.07	890	2	4.79
625	2	4.1	895	2	4.8
630	2	4.12	900	2	4.85
635	2	4.14	905	2	4.87
640	2	4.16	910	2	4.9
645	2	4.18	915	2	4.95
650	2	4.19	920	2	4.98
655	2	4.2	925	2	5.03
660	2	4.2	930	2	5.09
665	2	4.21	935	2	5.13
670	2	4.19	940	2	5.21
675	2	4.24	945	2	5.34
680	2	4.22	950	2	5.41
685	2	4.24	955	2	5.55
690	2	4.24	960	2	5.74
695	2	4.26	965	2	6.09
700	2	4.25	970	2	6.7
705	2	4.27	975	2	7.72
710	2	4.28	980	2	9.94
715	2	4.28	985	2	10.29
720	2	4.29	990	2	10.87
725	2	4.3	995	2	11.18
730	2	4.31	1000	2	11.41
735	2	4.31	1005	2	11.58
740	2	4.33	1010	2	11.73
745	2	4.34	1015	2	11.86
750	2	4.33	1020	2	11.95
755	2	4.35	1025	2	12
760	2	4.36	1030	2	12
765	2	4.37	1035	2	12
770	2	4.38	1040	2	12
775	2	4.39	1045	2	12
780	2	4.41	1050	2	12
785	2	4.42	1055	2	12
790	2	4.42	1060	2	12
795	2	4.44	1065	2	12

Time (s)	MV	PV
1070	2	12
1075	2	12
1080	2	12
1085	2	12
1090	2	12
1095	2	12
1100	2	12
1105	2	12
1110	2	12
1115	2	12
1120	2	12
1125	2	12
1130	2	12
1135	2	12
1140	2	12
1145	2	12
1150	2	12
1155	2	12
1160	2	12
1165	2	12
1170	2	12
1175	2	12
1180	2	12
1185	2	12
1190	2	12
1195	2	12
1200	2	12
1205	2	12
1210	2	12
1215	2	12
1220	2	12
1225	2	12
1230	2	12
1235	2	12
1240	2	12
1245	2	12
1250	2	12
1255	2	12
1260	2	12
1265	2	12
1270	2	12
1275	2	12
1280	2	12
1285	2	12
1290	2	12
1295	2	12
1300	2	12
1305	2	12
1310	2	12
1315	2	12
1320	2	12
1325	2	12
1330	2	12