PROCESS CONTROL SYSTEM IDENTIFICATION

By

NOR FAEIZAH BT MUSTAFA

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Universiti Teknologi Petronas
Bandar Seri Iskandar
31750 Tronoh
Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

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Nor Faeizah Muatafa

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(Assoc. Prof. Dr. Hj. Mohd Noh Karsiti)

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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 work is my own except as specified in the references and acknowledgement, and that the original work contained herein have not been undertaken or done by unspecific sources or person.

Faeizah

NOR FAEIZAH MUSTAFA

ABSTRACT

System identification is a method for generating workable dynamic response models based on an observed dataset from an actual system. It is used to give the input-output relationship of the dynamic response. The objective of this project is to design and implement System Identification for Liquid System Pilot Plant. The project will also make comparisons between the conventional and intelligent modeling technique. The project concentrates on the conventional technique known as empirical modeling and intelligent modeling by means of System Identification Toolbox. In empirical model building, models are determines by making small changes in the input variable about a nominal operating condition. The model developed by using this method provides the dynamic relationship between selected input and output variables. Matlab provides the System Identification Toolbox that helps to ensure the observed test data represents the dynamics of the system under investigation. It provides tools for creating mathematical models of dynamic systems based on the observed input-output data. For the intelligent technique, two model predictors, ARX and ARMAX, are used to obtain the best model. From the analysis, it shows that the ARX models exhibit quite the same characteristics as the models obtained from the empirical technique. By using the System Identification Toolbox, the ARMAX structures are the best models in representing the actual system. After model validation tests, all models from both the conventional and intelligent technique are capable of reproducing observed data with minimum predictive error.

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LIST OF ABBREVIATIONS

AR	=	Auto Regressive
ARX	=	Auto Regressive with eXternal input
ARMAX	=	Auto Regressive Moving Average with eXternal input
FYP	=	Final Year Project
GUI	=	Graphical User Interface
MV	=	Manipulated Variable
P	=	Proportional Mode
PI	=	Proportional Integral Mode
PID	=	Proportional Integral Derivative Mode
PV	=	Process Variable
P&ID	=	Piping & Instrument Diagram
SISO	=	Single Input Single Output
SP	=	Set Point

CHAPTER 1
INTRODUCTION

1.1 Background of Study

System Identification is a process of generating workable models of dynamic response based on observed dataset from the actual system [1]. It is used to give the input-output relationship of the dynamic response. The behavior of the input and output data of a system can be used to design and implement a feed-forward or an open loop control.

For this project, in the first semester, it is required to study the theory of system identification and the use of MATLAB in system modeling. This involves familiarization with MATLAB's System Identification toolbox, which covers data recording, model structuring, determination of the best model and model validation.

Since System Identification is based on observed input and output data of a system, the dataset is very important. For simplicity, a dataset that consists of a single input and a single output (SISO) is used, as shown in figure 1.1.

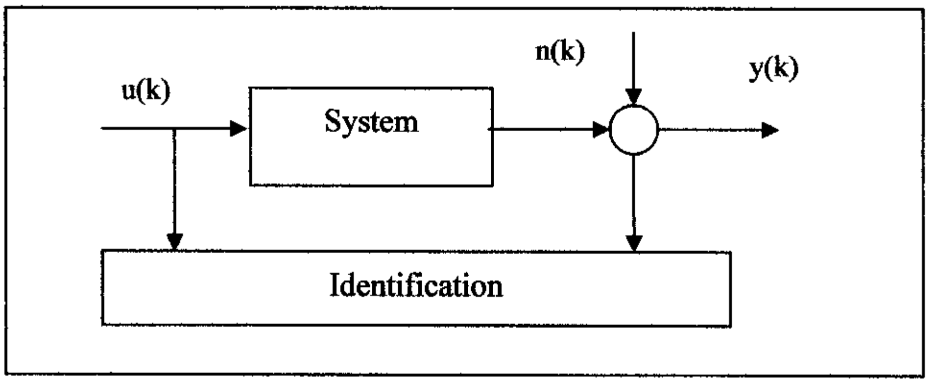

Figure 1.1 The System Identification Process

1.2 Problem Statement

1.2.1 Problem Identification

The objective of this project is to design and implement a selected process control system from one of the existing pilot plants using system identification techniques. The Liquid System Pilot Plant has been chosen for this project. The main task is to gather real-time data and apply both the conventional and intelligent techniques of System Identification.

The performance result of the conventional technique is then being further improved by means of intelligent methods. This consists of two model predictors, which are the ARX (Auto Regressive with eXternal input) Model and ARMAX (Auto Regressive Moving Average with eXternal input) Model.

1.2.2 Significance of the Project

In a real industrial application, variables in a chemical process exhibit strong correlations created by the process itself as well as the feedback controllers. The correlations are typically dynamic and non-linear. Conducting a study using System Identification will help the author to appreciate the art of building a mathematical model to represent a particular system. Having the knowledge of deducing a mathematical model by studying the behavior of the input and output data will be very helpful in optimizing a process control system.

A good model will be able to estimate responses of the existing dynamic system. A model that accurately captures the correlations can be useful in many applications including process monitoring, software sensor integration and predictive control. Thus, this project has a very wide area of application.

1.3 Objective and Scope of Study

1.3.1 Objectives of Study

The main objectives of this study are:

1. To gather real-time data and apply both the conventional and intelligent System Identification techniques for the Liquid System Pilot Plant.
2. To simulate the estimated model constructed in MATLAB
3. To analyze and compare the modeling technique using System Identification Toolbox with conventional modeling for better performance determination.

1.3.2 Scope of Study

The scope of this study will be to model a single temperature control loop for a product heat exchanger of the Liquid System Pilot Plant using System Identification methods.

1.3.3 Feasibility of the Project

A time management plan has been outlined for the project. Time management is important to give equal attention to each task. It is essential to ensure that the project is feasible and can be implemented within the allocated time frame. Generally, project time is divided as follows - 10% of the time is spent on literature review, 30% for designing purposes, 50% for setting up the experiments, including the analysis and 10% for compiling all the findings.

CHAPTER 2

LITERATURE REVIEW

2.1 Control System

Figure 2.1 shows a dynamic system with three basic elements, which are input (u), output (y) and noise (e). Noise is also known as the disturbance of the system. A control system provides an output or response for a given input or stimulus. The input represents the desired response, while the output is the actual response. There are two control system configurations, which are open loop and closed loop systems.

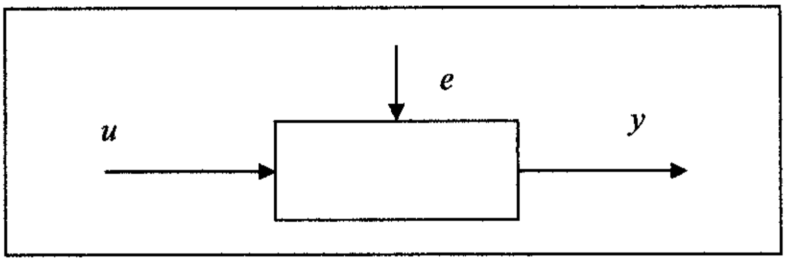

Figure 2.1 Input-Output System Configurations with Noise.

An open loop system (see figure 2.2) consists of a subsystem called an input transducer which converts the input signal into a form that is used by the controller. Then the controller drives the process or plant. The input is also called the 'reference' while the output is also called the 'controlled variable'. The distinguishing characteristic of an open loop system is that it cannot compensate for any disturbance that is added to the controller's driving signal. As a result, the output will be corrupted by the effect of noise.

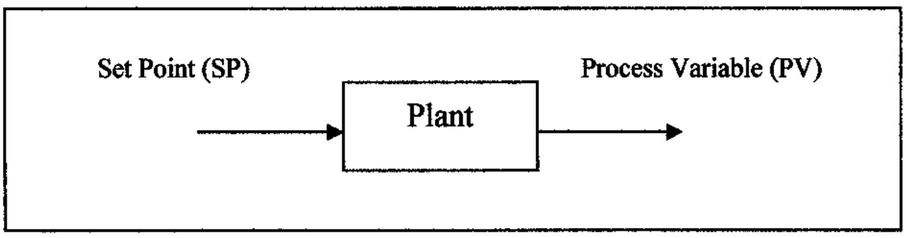

Figure 2.2 An Open Loop System

The disadvantages of an open loop system can be overcome by using a closed loop system (see figure 2.3). In a closed loop system, the input transducer converts the form of the input to the form used by the controller. An output transducer, or also known as sensor, measures the output response and converts it into the form used by the controller. The closed loop system compensates any disturbances by measuring the output response, feeding that measurement back through a feedback path, and comparing that response to the input at the summing junction. If there is a difference between the two responses, the system drives the plant by actuating signal to make a correction. If there is no difference, the system will not drive the plant since the plant's response is already at the desired value.

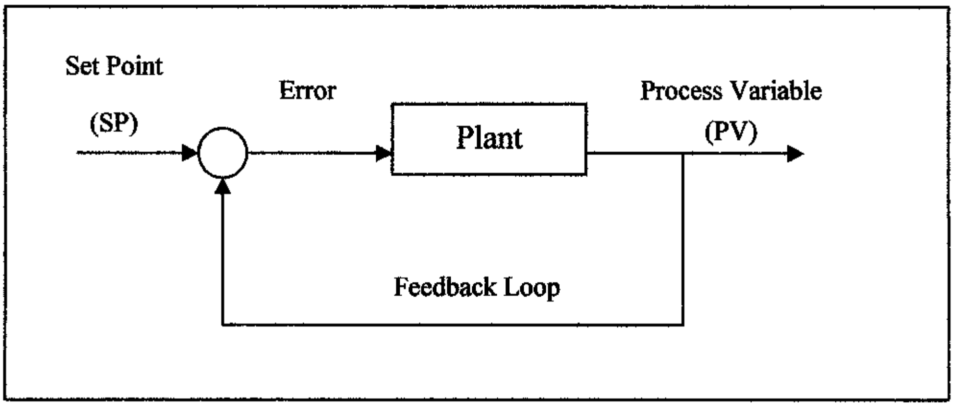

Figure 2.3 A Closed Loop System

2.2 System Identification

System identification is a method to build mathematical models of a dynamic system based on measured inputs and outputs of a system as shown in figure 2.4. Using this model, the response of the actual system can be simulated. This is done by manipulating the parameters of the particular model until the output value is as close as the actual measured outputs. There are several methods or models available that can be used for system identification. Each of the methods has its own approach in obtaining an output which is as close to the actual measured values. A good model will give a small error when compared to the real system.

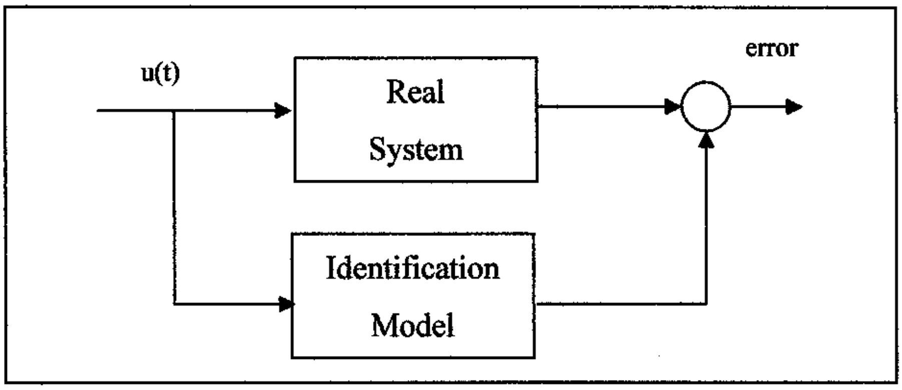

Figure 2.4 General System Identification Model

2.3 Basic Elements for Plant Control Loop

The basic elements of a control loop are as shown in figure 2.5. It consists of the sensor stage, transducer stage, signal conditioning, measured parameters and controller.

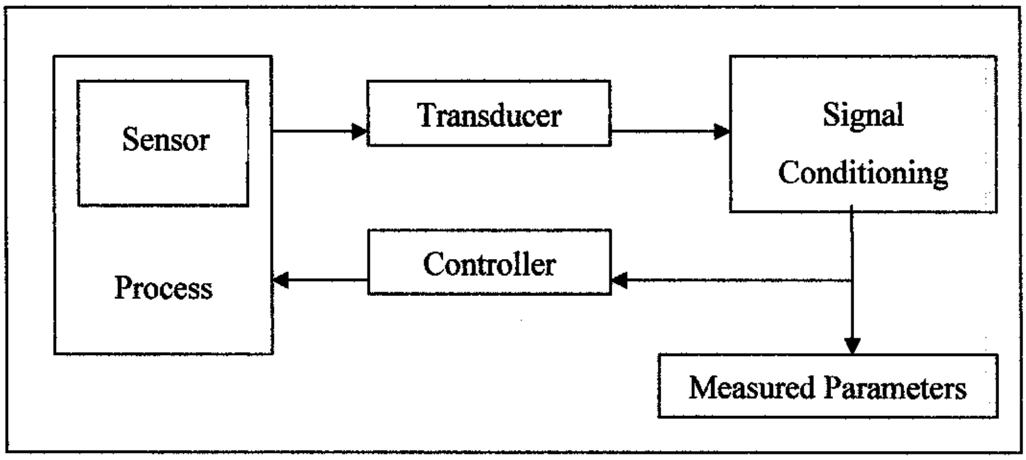

Figure 2.5 The basic elements for plant control loop.

The sensor stage senses the variable that is being measured. The selection, placement and installation of the sensor are important. This is because the input of the feedback control system is the information or data sensed by the sensor.

For the transducer stage, a transducer or a transmitter converts the sensed information into detectable signal form such as mechanical, electrical or optical signal. It converts the sensed information into a form that can be easily quantified.

Signal conditioning plays an important role by taking a signal from the transducer and modifies it into desired form. The modification of the signal can be done by increasing the magnitude of the signal through amplification or by removing some portions of the signal through filtering. The signal conditioning stage also provides mechanical or optical linkage between the transducer and output stage.

The most critical part in the system is the control stage. It interprets the measured signal and compares it to the desired value. Based on this, the controller reacts to control the process. The controller's role is to ensure that the measured and desired output is as close as possible. There are three types of controller that are widely used, which are the P Controller (Proportional Mode), PI (Proportional-Integral Mode) Controller and PID (Proportional-Integral-Derivative Mode) Controller. Each of them exhibits different characteristics. However, the main goal of using them are the same, which is to maintain the process variable as close as possible to the desired value.

2.4 Empirical Modeling

The purpose of plant modeling is to establish a relationship between parameters in the physical systems and the transient behavior of the system. There are two ways in modeling a plant; by mathematical or by empirical (experimental) approach as shown in figure 2.6.

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

However, the mathematical approach has limitations, which can often results from the complexity of mathematical models used. Modeling realistic processes requires a large engineering effort to formulate the equations, determine all parameter values and solve the equations, usually through numerical methods. Therefore, an alternative modeling method, termed as empirical modeling, can be used instead for plant process control.

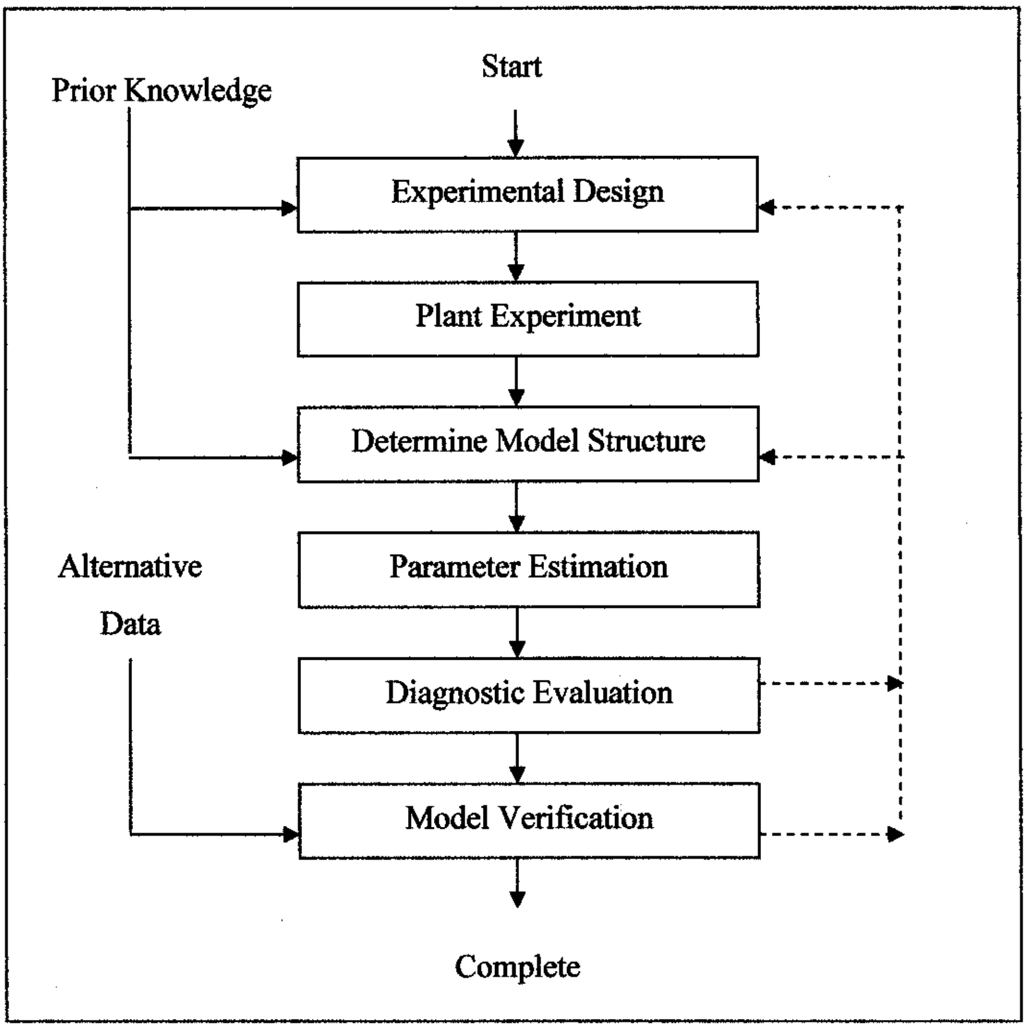

Figure 2.6 Procedures for Empirical Transfer Function Model Identification

2.5 Pilot Plant Process (TIC-634)

The plant which is used in this project is a scaled down Liquid-phase Temperature Process Pilot Plant (model SIM305-TT-BATCH). It is a self-contained unit designed to simulate real processes found in industrial plants. The simulation can be used for the study of the measurement and control of various temperature processes. The P&ID of the pilot plat is attached in Appendix III.

The process loop for this project is the TIC-634 loop which involves the Temperature Transmitter (TT 634), Temperature Controller (TIC 634) and Temperature Control Valve (TY 634). This loop controls the temperature inside the Heat Exchanger (HE620). Figure 2.7 shows the loop drawing of TIC-634. The loop drawing provides information on equipment, piping, valves and instrumentation interfacing and connection.

The loop drawing enables us to view the connections of the instruments and relate it to the actual process. For the Process Control System Identification project, the project scope shall only cover a single Temperature Control loop, TIC-634, which regulates product temperature using a heat exchanger. All items are identified using a standard numbering system, which complies with the PETRONAS Technical Standards.

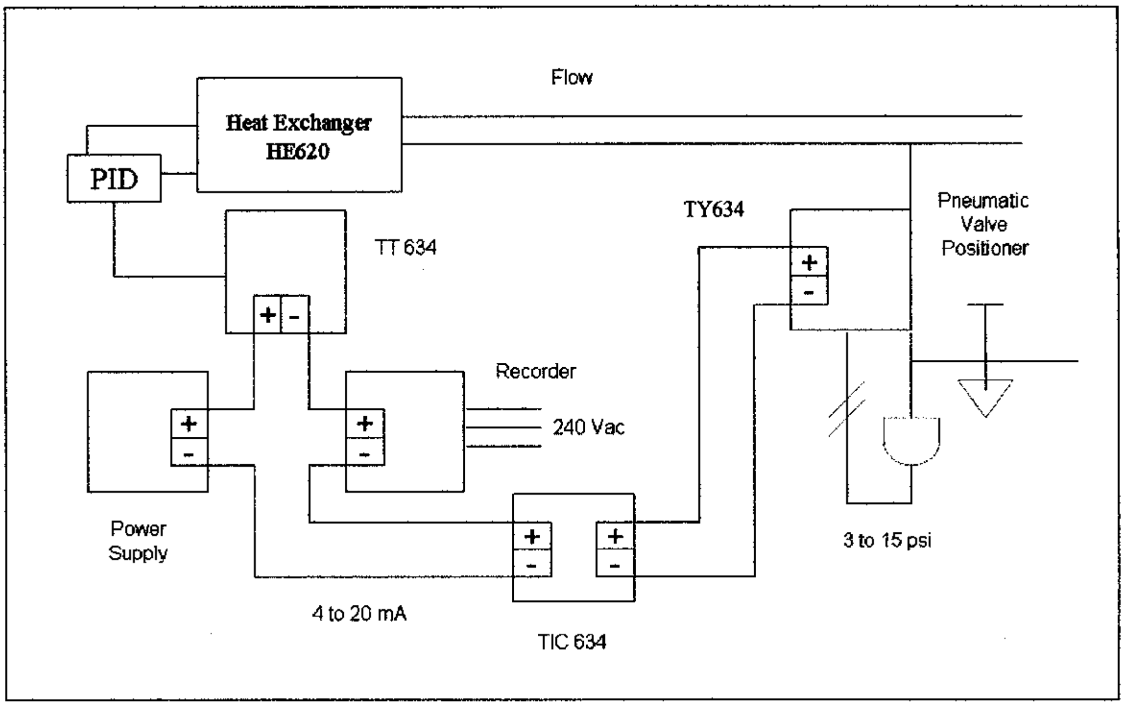

Figure 2.7 Loop Drawing for Temperature Control Pilot Plant.

The feedback control makes use of the output of the system to influence an input to the same system as shown in figure 2.8. There are several reasons for controlling the system. The first reason is to maintain product temperature (raw water) at the desired value. The control system will control the valve (by opening or closing) in response to a change in the disturbance variable. The second reason is to respond to a change in the desired value.

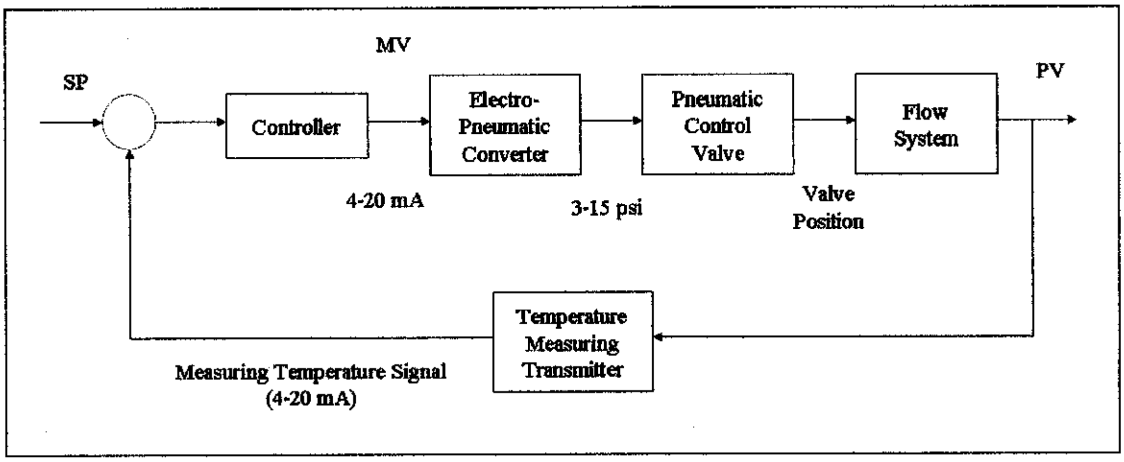

Figure 2.8 Temperature Control Loop

CHAPTER 3
METHODOLOGY

3.1 Procedure Identification

The purpose of System Identification is to obtain a mathematical model of a system from actual data. The System Identification process involves the construction of a model from actual data and model validation. The construction of a model requires three basic components, which are data records, model structure and determination of the best model. The system identification process flow is shown in figure 3.1.

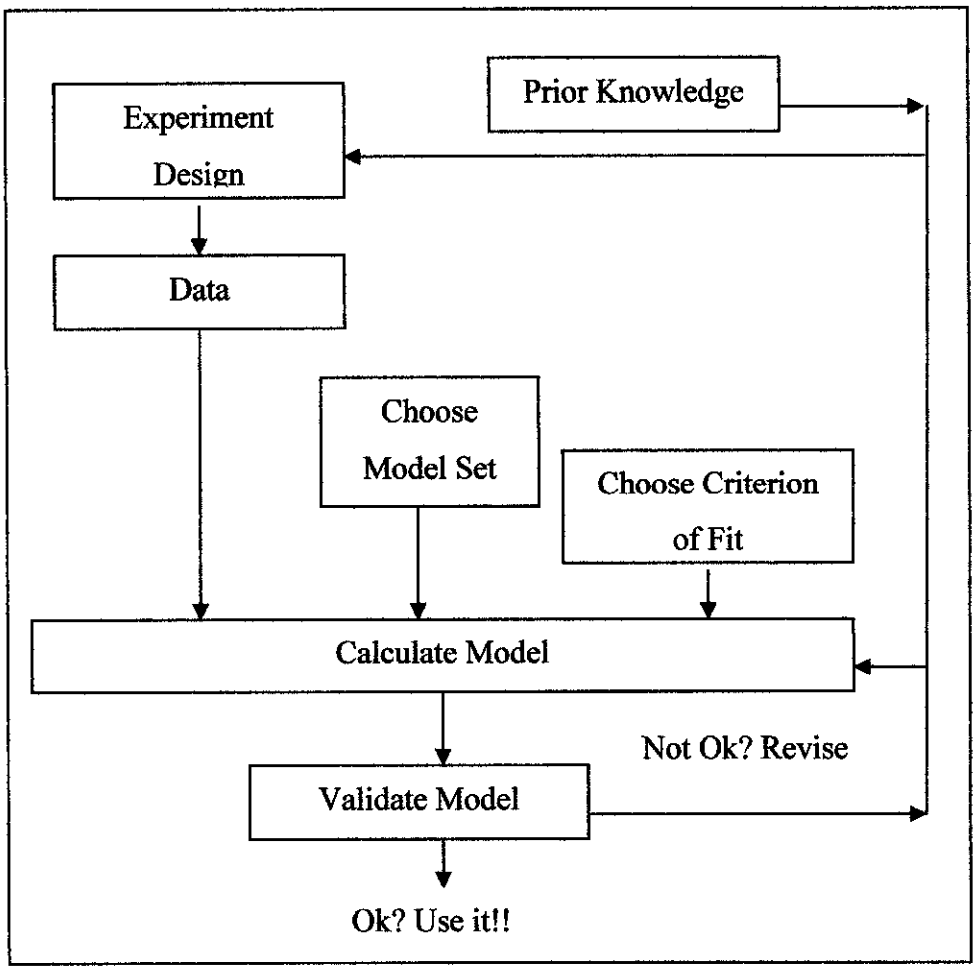

Figure 3.1 System Identification Procedures

The first step in System Identification is the selection of a model class based on prior knowledge, the objective and the actual data. The next step is designing the input, experimentation and data collection followed by parameterization of the model class based on realization theory and selection of the best element in the model class. The final step is evaluation of the quality of the selected model with respect to the objective. This project is focused mainly on modeling, simulating and analyzing the dynamic system.

3.2 Empirical Modeling

Empirical identification is an efficient alternative modeling method specifically designed for process control. The model developed by using this method provides the dynamic relationship between selected input and output variables. For this particular project, the empirical model can be used to relate temperature to the valve opening.

In empirical model building, models are determined by making small changes in the input variable about a nominal operating condition. The resulting dynamic response will be used to determine the model. This general procedure is an experimental linearization of the process that is valid for some region about the nominal condition.

The empirical method involves carrying out designed experiments, during which the process is perturbed to generate dynamic data. The success of the methods requires close adherence to principles of experimental design and model fitting. Two identification methods are available; the first method is termed the process reaction curve which employs simple graphical procedures for model fitting. The second method employs statistical principles for determining the parameters.

3.3 System Identification Toolbox

The System Identification Toolbox provides a graphical user interface (GUI). The GUI covers most of the toolbox's functions and gives easy access to all variables that are created during a session.

3.3.1 Estimating models

Estimating models from data is the central activity in the System Identification Toolbox. One can distinguish between two different types of estimation methods:

1. Direct estimation of the Impulse or the Frequency Response of the system. These methods are often also called nonparametric estimation methods, and do not impose any structure assumption about the system, other than that it is linear.
2. Parametric methods. A specific model structure is assumed, and the parameters in this structure are estimates using the data. This opens up a large variety of possibilities, corresponding to different ways of describing the system. Dominating ways are state-space and several variants of difference equation descriptions.

3.3.2 Examining models

The models that have been estimated are then being examined, compared with other models, and tested with new dataset. This is done by using two functions as follows:

1. Transient response - shows the plot of the transient response of the selected models.
2. Model output - shows the plot of the simulated (predicted) outputs of selected models.

CHAPTER 4
RESULTS & FINDINGS

4.1 Process Identification & Open Loop Tuning Method

Open loop response test was carried out in order to enable the author to determine the process time constant, process gain and process dead-time. The variables involved in the test are; the Process Variable (PV), Manipulated Variable (MV) and Set Point (SP). For this experiment, PV is the temperature rate and MV is the valve opening in percentage. The measurement unit for the temperature rate is degree Celsius (^{o}C) and for the valve opening it is in percent (%). A small change is applied to the MV (as input) to generate a dynamic response of PV (as output). The actual dataset of the open loop tuning is attached in the Appendix I.

4.2 Process Reaction Curve Method

The process reaction curve is the reaction of the process to a step change in its input signal. In general, a process reaction curve can be determines as follows:

1. Allow the process to reach steady state
2. Introduce a single step change in the input variable
3. Collect input and output response data until the process reaches steady state again
4. Perform the graphical process reaction curve calculations

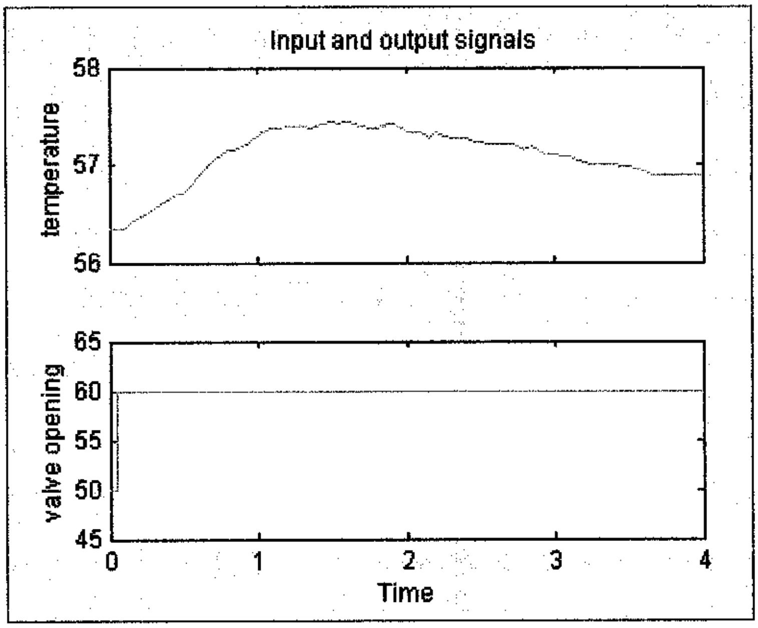

Figure 4.1 The actual dataset plot

Table 4.1 Result for open loop tuning

Measurement	***Test 1***
Change in Manipulated Variable, dM	10%
Change in Ultimate Value, dB_u	0.55°C
Apparent Time Constant, T	1.87min
Apparent Dead Time, T_d	0.34min
Calculations:	
Steady State Process Gain $Kp=dB_u/dM$	5.5
$R=T_d/T$	0.182

The graphical calculations determine the parameters for a first-order-with-dead-time model since the process reaction curve is restricted to this model only. The form of the model is given by:

$$Y(s)/X(s) = (K_p e^{-\theta s})/(\tau s = 1) \tag{4.1}$$

There are two graphical techniques in common use. The first technique is adapted from Ziegler and Nicholas (1942) [4], and uses graphical calculation. The intermediate values determined from the graph are magnitude of the input (δ), the magnitude of the steady state change in the output, (Δ), and the minimum slope of the output-versus-time plot, S. The maximum slope occurs at $t=\theta$, and therefore $S=\Delta/\tau$. Thus, the model parameters can be calculated as:

$$K_p = \Delta / \delta$$

$$\tau = \Delta / S$$

$$\theta = \text{Intercept of maximum slope with initial value}$$

The second technique also uses graphical calculations. The intermediate values determined from the graph are the magnitude of the input change (δ), the magnitude of the steady state change in the output (Δ), and the times at which the output reached 28% and 63% of its final value. Any of the two values can be selected to determine the unknown parameters, θ and τ. The typical times are selected where the transient response is changing rapidly so that the model parameters can be accuratcly determined in spite of noise measurement.

$$Y(\theta+\tau) = \Delta(1-e^{-1}) = 0.632\Delta \tag{4.2}$$

$$Y(\theta+\tau/3) = \Delta(1-e^{-1/3}) = 0.283\Delta \tag{4.3}$$

Thus, the values of time at which the output reaches 28.3% and 63.2% of its final value can be used to calculate the model parameters.

4.2.1 Method 1

$$\delta = 0.1$$

$$\Delta = 0.55$$

$$K_p = (0.55)/(0.1) = 5.5$$

$$S = 0.29$$

$$\tau = \Delta/S = (0.55)/(0.29) = 1.87$$

$$\theta = 0.34$$

The model transfer function is:

$$\frac{Y(s)}{X(s)} = \frac{K_p e^{-\theta s}}{\tau s + 1}$$

$$T(s) = \frac{5.5e^{-0.34s}}{(1.87s + 1)}$$

4.2.2 Method 2

$$\delta = 0.1$$

$$\Delta = 0.55$$

$$0.63\Delta = 0.63(0.55) = 0.347$$

$$t_{63\%} = 1.87$$

$$0.28\Delta = 0.28(0.55) = 0.154$$

$$t_{28\%} = 0.85$$

$$\tau = 1.5(t_{63\%} - t_{28\%}) = 1.53$$

The model transfer function is:

$$\frac{Y(s)}{X(s)} = \frac{K_p e^{-\theta s}}{\tau s + 1}$$

$$T(s) = \frac{5.5e^{-0.34s}}{1.53s + 1}$$

4.3 System Identification Toolbox

The System Identification Toolbox supports a wide range of model structures for linear systems. They are all typically six choices but for this project, two commonly used structures have been selected which are the ARX and ARMAX models.

4.3.1 ARX Models

The ARX models can be described as a rational functions q^{-1} and specify the numerator and denominator coefficients. A commonly used parametric model is the ARX model that corresponds to:

$$G(q) = q^{-nk} . \frac{B(q)}{A(q)} \qquad H(q) = \frac{1}{A(q)} \tag{4.4}$$

Where B and A are polynomials in the delay operator q^{-1}:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + ... + a_{na} q^{-na} \\ B(q) &= b_1 + b_2 q^{-1} + ... + b_{nb} q^{-nb+1} \end{aligned} \tag{4.5}$$

Here, the numbers *na* and *nb* are the orders of the respective polynomials. The number *nk* is the number of delays from input to output.

The measured and simulated model outputs are shown in Figure 4.2. The figure represents 3 ARX models with different order and the actual dataset plot or the measured model output. These are the output of the model when the input is a step.

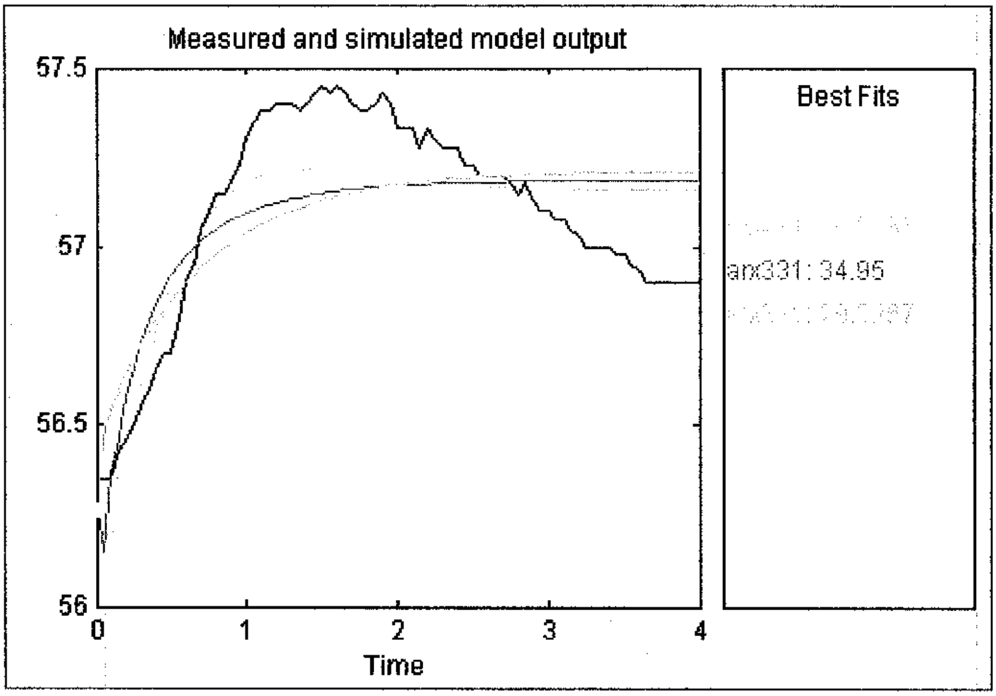

Figure 4.2 Transient Response for ARX Models

The orders and percentage of best fit for all three models are stated at the right hand column of the figure. The orange, blue and green lines represent the ARX models of order 4, 3 and 2 respectively. The black line represents the measured output model. All four models have 80 numbers of samples and are sampled at 0.05 sampling interval.

4.3.2 ARMAX Models

Another very common and more general model structure is the ARMAX. The parametric model structure for ARMAX model is as follows:

$$A(q)y(t) = B(q)u(t-nk) + C(q)e(t) \tag{4.6}$$

Where A, B and C are polynomials in the delay operator q^{-1}:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \ldots\ldots + a_{na} q^{-na} \\ B(q) &= b_1 + b_2 q^{-1} + \ldots\ldots + b_{nb} q^{-nb+1} \\ C(q) &= 1 + C_1 q^{-1} + \ldots\ldots + C_{nc} q^{-nc} \end{aligned} \tag{4.7}$$

Here, the numbers *na, nb* and *nc* are the orders of the respective polynomials.

The measured and simulated model outputs are shown in Figure 4.3. The figure represents 3 ARMAX models with different order and the actual dataset plot or the measured model output. These are the output of the model when the input is a step.

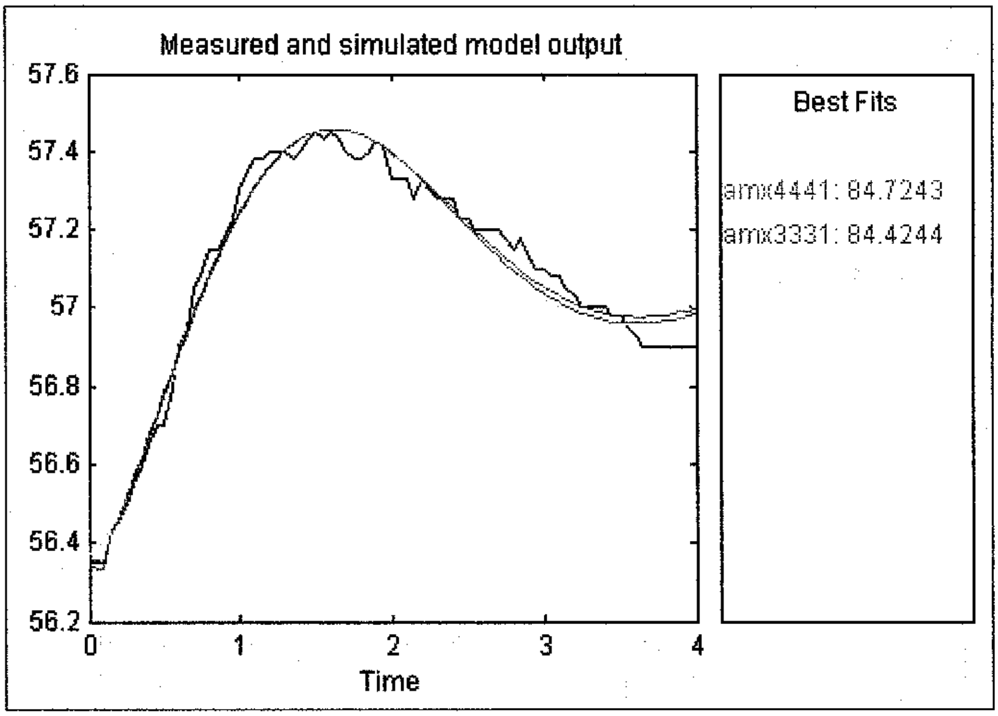

Figure 4.3 Transient Response for ARMAX models

The orders and percentage of best fit for all three models are stated at the right hand column of the figure. The blue, red and gold lines represent the ARMAX models of order 4, 3 and 2 respectively. The black line represents the measured output model. All four models have 80 numbers of samples and are sampled at 0.05 sampling interval.

4.4 Findings

From the result obtained, it shows that the empirical modeling gives a linear relationship between the input and output values. Although it does not provide enough information to satisfy the analysis requirements, a linear transfer function model developed using this method are adequate for the project implementation.

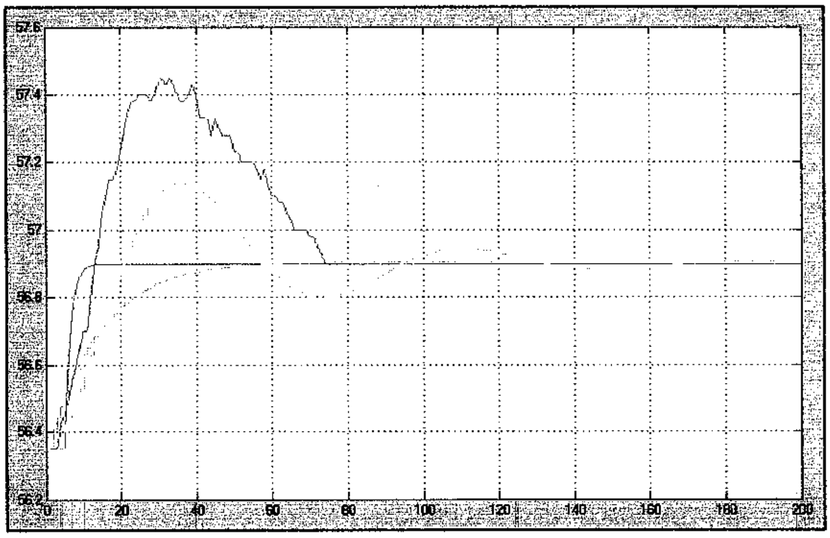

Figure 4.4 Models Output

From Figure 4.4, it shows that ARX and empirical models exhibit quite the same characteristics since the ARX structures produce quite similar model output as the empirical models. The simulation results clearly show that ARMAX structures are the best models in reproducing the actual system apart from the models obtained from ARX and empirical modeling.

The model errors for both conventional and intelligent techniques are obtained by calculating the area under the graphs. Therefore, the model errors for all models are as follows.

1. Model error for empirical structure:

$$\left|\frac{34-38.5}{38.5}\right| \times 100 \approx 11.69\%$$

2. Model error for ARX structure:

$$\left|\frac{33-38.5}{38.5}\right| \times 100 \approx 14.29\%$$

3. Model error for ARMAX structure:

$$\left|\frac{35-38.5}{38.5}\right| \times 100 \approx 9.09\%$$

The acceptable range for model error in process control is within 20% [4]. Based on the calculation above, model errors for all three models are within the acceptable range. Therefore, it can be said that all the models are validated and are capable of reproducing the actual system with small predictive error.

CHAPTER 5
MODEL VALIDATION & DISCUSSION

5.1 Model Validation for Conventional Method

5.1.1 Method 1

Model validation is performed to check whether the models obtained in the previous part are capable of reproducing the actual system or not. For this part, Matlab Simulink is used in order to produce the output responses.

From the first method, the transfer function is:

$$T(s) = \frac{5.5e^{-0.34s}}{1.87s+1}$$

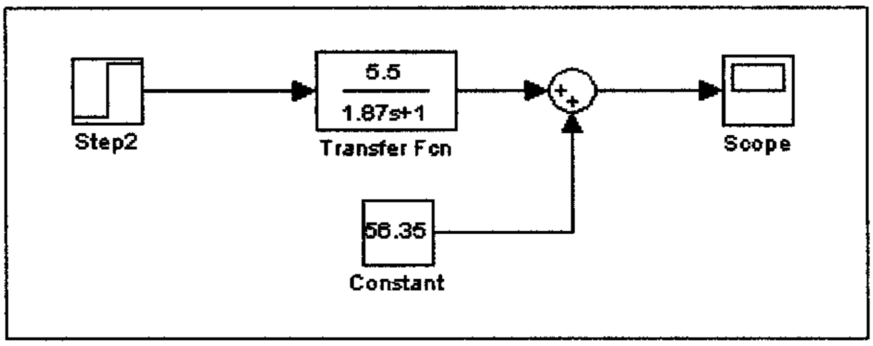

Figure 5.1 Model validations for empirical modeling (Method I)

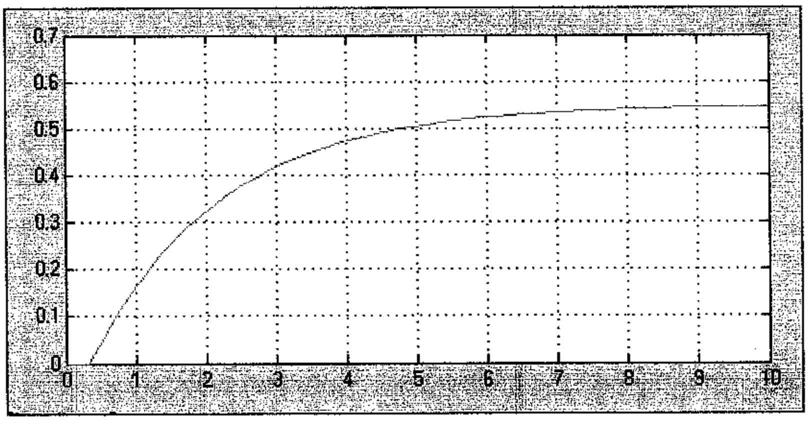

Figure 5.2 Model validation result for empirical modeling (Method I)

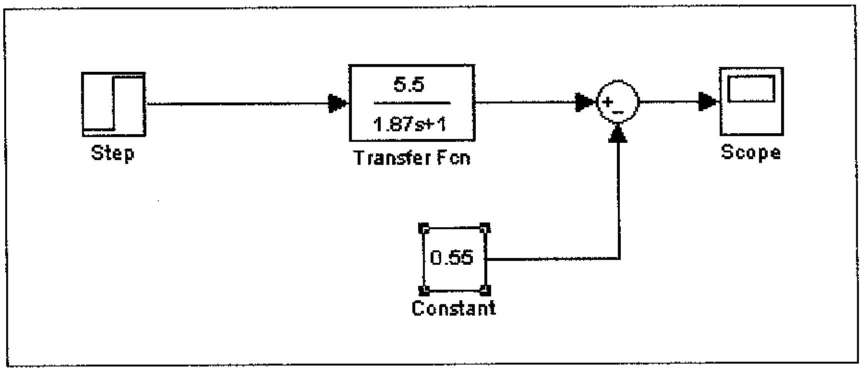

Figure 5.3 Error comparison between actual value and empirical modeling (Method I)

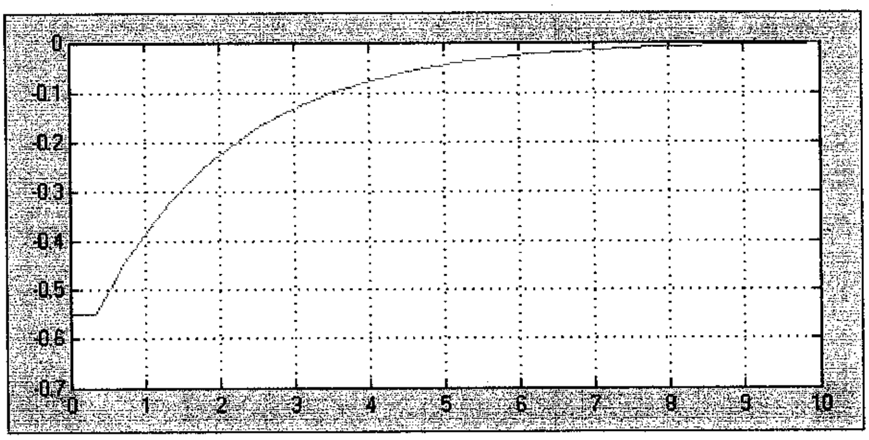

Figure 5.4 Error comparison result for empirical modeling (Method I)

5.1.2 Method 2

By using the transfer function obtained in the previous chapter, the same technique is applied for the second method.

$$T(s) = \frac{5.5e^{-0.34s}}{1.53s + 1}$$

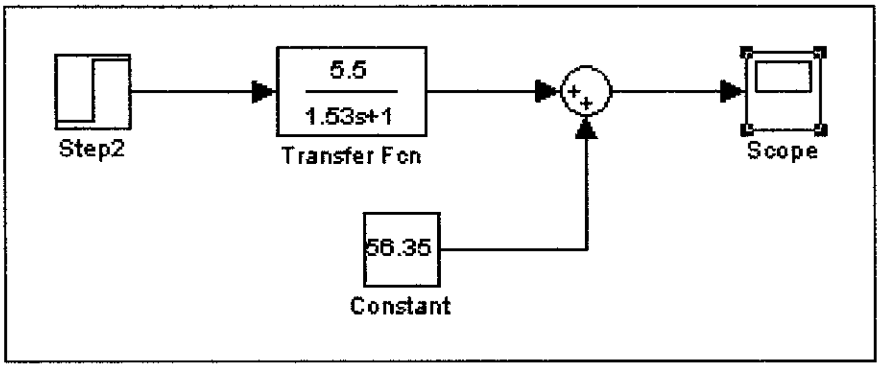

Figure 5.5 Model validations for empirical modeling (Method II)

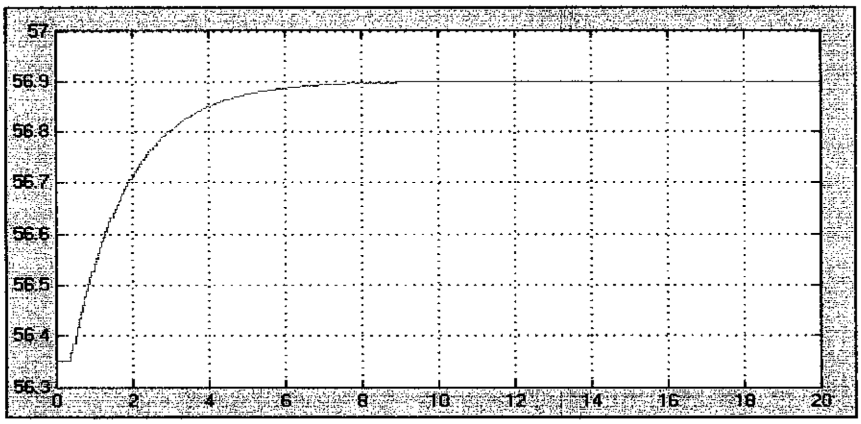

Figure 5.6 Model validation result for empirical modeling (Method II)

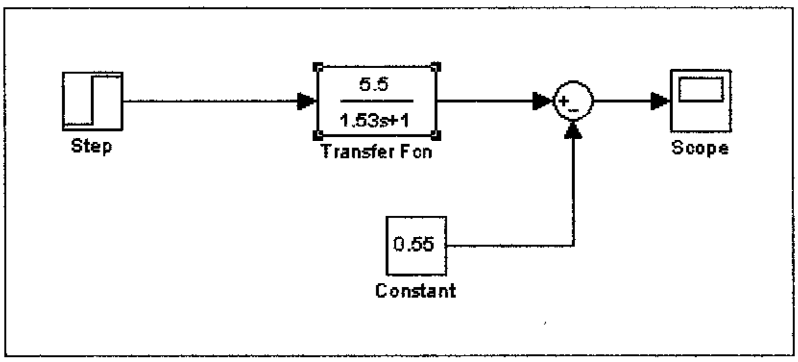

Figure 5.7 Error comparison between actual value and empirical modeling (Method II)

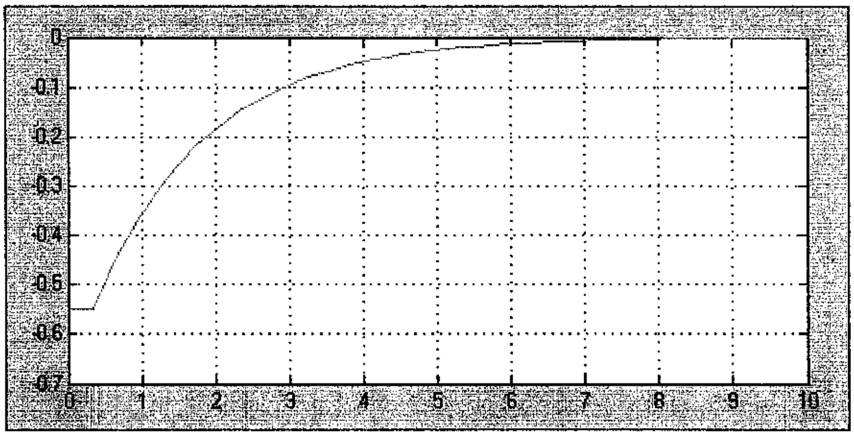

Figure 5.8 Error comparison result for empirical modeling (Method II)

After all the models have been tested, the results show that both models obtained from conventional techniques are validated. Models are capable of reproducing the measured output of the actual system.

5.2 Model Validation for Intelligent Method

5.2.1 ARX Models

Same technique is used for validating the intelligent technique. The graphs obtained from the Matlab Simulink are then being used to calculate the error of the models.

For the ARX models, the discrete transfer function obtained are as follows:

1. ARX model of order 2:

$$G(z) = \frac{0.03501z + 0.003495}{z^2 - 1.358z + 0.3989}$$

2. ARX model of order 3:

$$G(z) = \frac{0.01645z^2 + 0.01645z - 0.005599}{z^3 - 1.252z^2 - 0.0236z + 0.304}$$

3. ARX model of order 4:

$$G(z) = \frac{0.009255z^2 + 0.009255z + 0.009255}{z^4 - 1.168z^3 - 0.02256z^2 - 0.03517z + 0.2547}$$

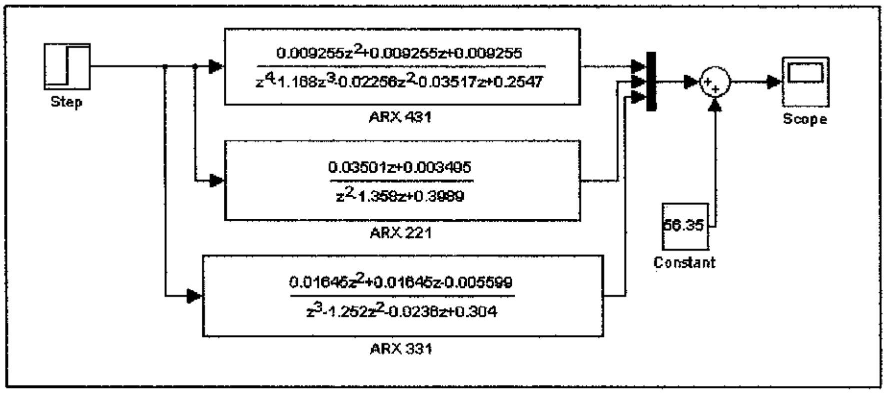

Figure 5.9 Model validations for ARX structures

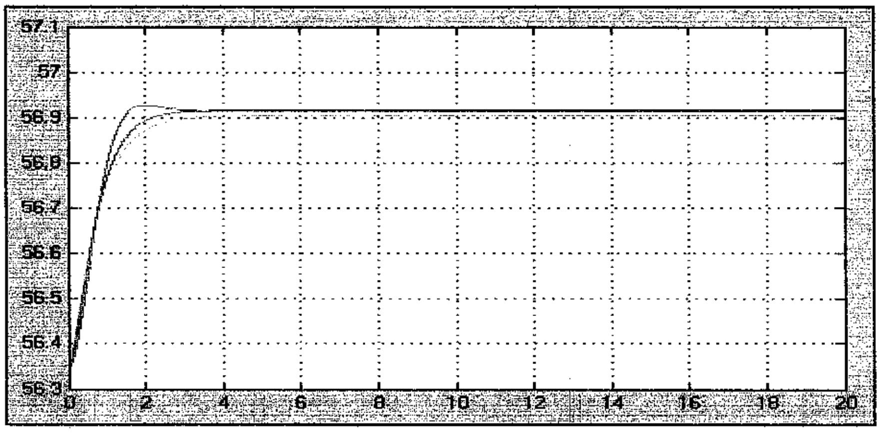

Figure 5.10 Model validation results for ARX structures

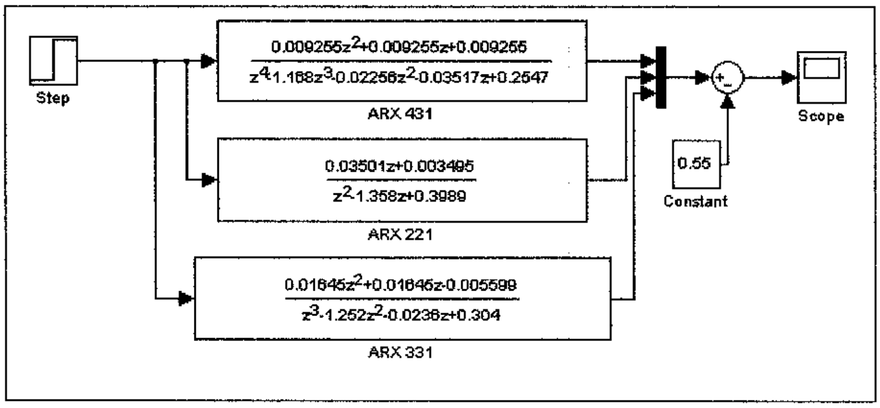

Figure 5.11 Error comparison between actual value and ARX structures

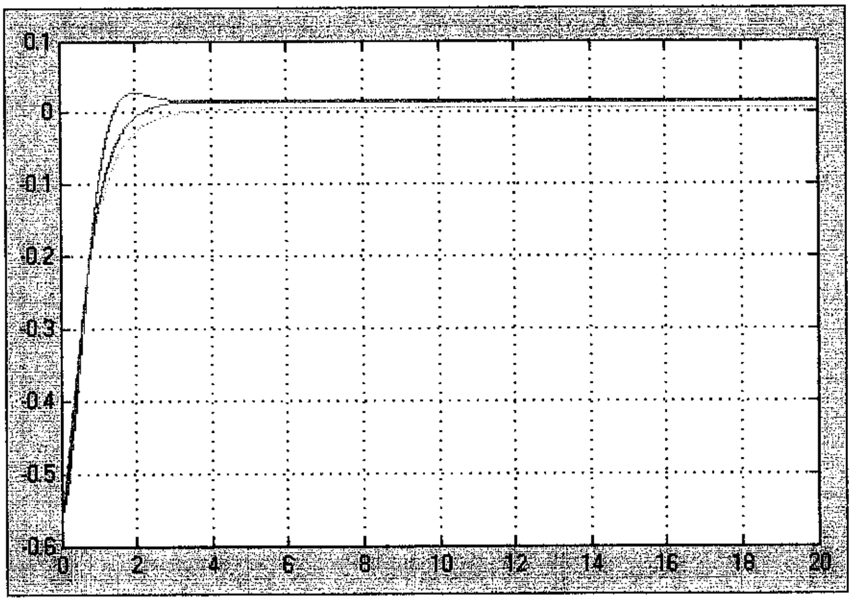

Figure 5.12 Error comparison results for ARX structures

In Figure 5.11 and 5.12, the green, red and blue lines represent the ARX models of order 2, 3 and 4 respectively. Referring to Figure 5.11, the steady-state point of ARX models for order 2, 3 and 4 are slightly above the set point. The set point of the system is 0.55, and therefore, the model errors of these structures are:

1. ARX model of order 2

$$\frac{0.56-0.55}{0.55}\times 100\% = 1.82\%$$

2. ARX model of order 3

$$\frac{0.57-0.55}{0.55}\times 100\% = 3.64\%$$

3. ARX model of order 4

$$\frac{0.57-0.55}{0.55}\times 100\% = 3.64\%$$

The acceptable range of model error in process control is within 5% [4]. Thus, the validation tests give realistic results since the errors of all three models are much less than 25%. Therefore it can be said that all of the models are validated and are capable of reproducing the actual system with small predictive error.

5.2.2 ARMAX Models

For the ARMAX models, the discrete transfer function obtained are as follows:

1. ARMAX model of order 2:

$$G(z) = \frac{0.01006z - 0.003064}{z^2 - 1.948z + 0.9555}$$

2. ARMAX model of order 3:

$$G(z) = \frac{0.02954z^2 - 0.01232z - 0.006793}{z^3 - 1.318z^2 - 0.2684z + 0.5972}$$

3. ARMAX model of order 4:

$$G(z) = \frac{0.02963z^3 + 0.0005519z^2 - 0.01423z - 0.001245}{z^4 - 1.044z^3 - 0.3692z^2 + 0.02171z + 0.4068}$$

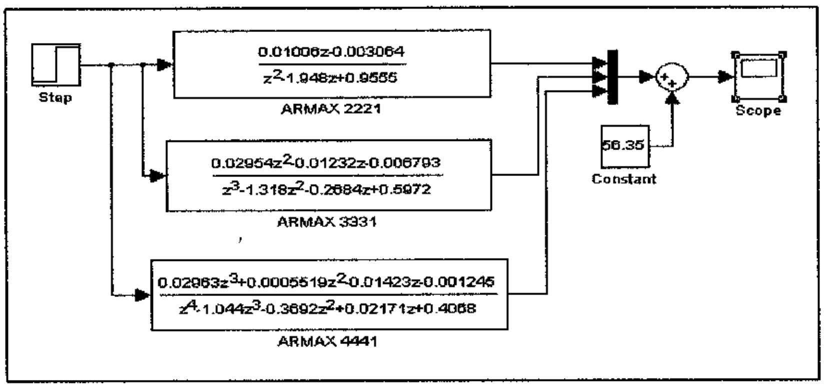

Figure 5.13 Model validation for ARMAX structures

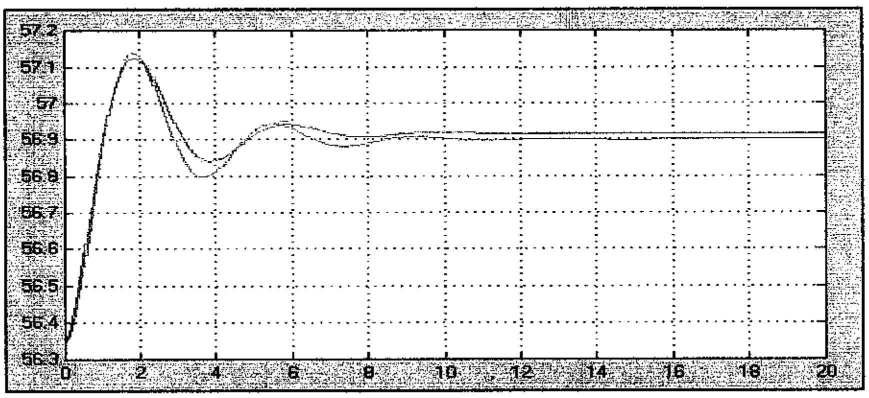

Figure 5.14 Model validation results for ARMAX structures

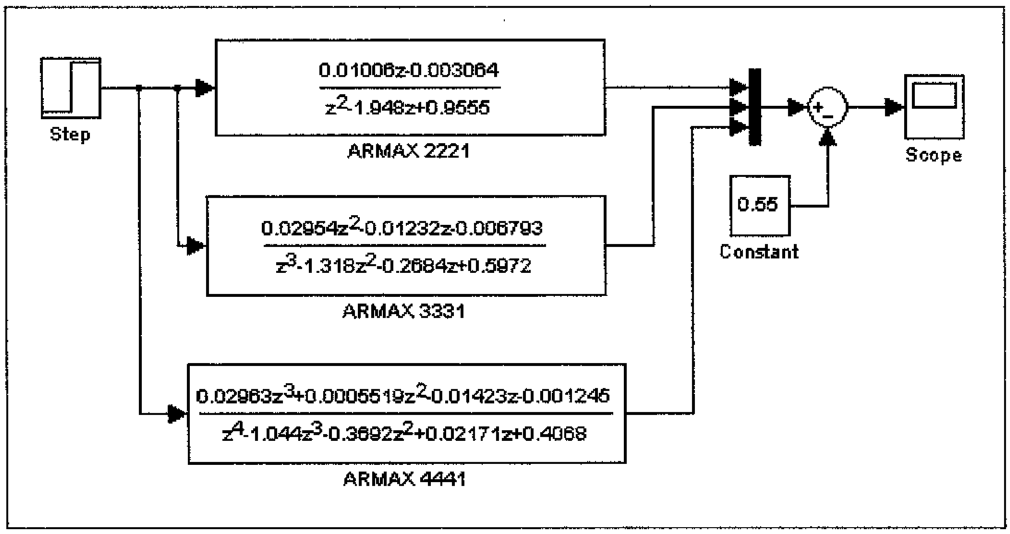

Figure 5.15 Error comparison between actual value and ARMAX structures

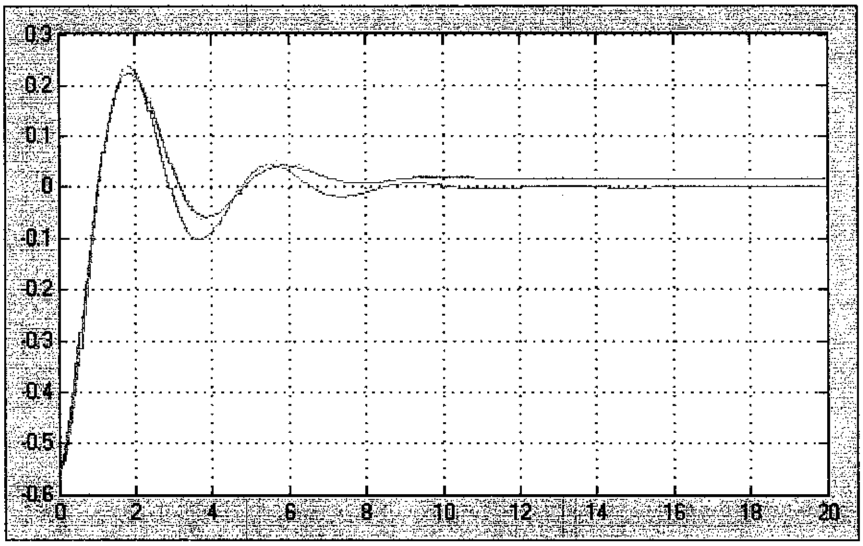

Figure 5.16 Error comparison results for ARMAX structures

In Figure 5.14 and 5.16, the blue, red and green lines represent the ARMAX models of order 2, 3 and 4 respectively. Referring to Figure 5.16, the steady-state point for ARMAX models of order 3 and 4 are slightly above the set point. Only ARMAX model of order 2 steady states at the set point and therefore, the steady-state errors of these models are:

1. ARMAX model of order 2

$$\frac{0.55-0.55}{0.55}\times 100\% = 0\%$$

2. ARMAX model of order 3

$$\frac{0.57-0.55}{0.55}\times 100\% = 3.64\%$$

3. ARMAX model of order 4

$$\frac{0.57-0.55}{0.55}\times 100\% = 3.64\%$$

Based on the calculation above, the errors of all three models are less than 5%, which is the acceptable range of model error. Therefore, it can be said that all of the models are validated and are capable of reproducing the actual system with small predictive error.

5.3 Discussion

There are many techniques available in System Identification. The method that will be discussed in this section is the empirical modeling and intelligent modeling technique. The intelligent modeling technique that has been chosen to be used in this project is by using the Matlab System Identification Toolbox.

Empirical identification is an efficient alternative modeling method specifically designed for process control. It is an iterative procedure which requires the execution of several experiments and the evaluation of potential model structures before a model can be been determined. The models developed using this method provides a dynamic relationship between the selected input and output variables.

For this particular project, the empirical model is able to relate the rate of temperature to the valve opening in percentage. Although the empirical model is tailored to specific need of the process control, it does not provide enough information to satisfy all process design and analysis requirements and therefore, cannot replace a model derived from fundamental principles. Another limitation of empirical modeling is it is limited to first order with dead time systems only. Due to this limitation, the model obtained from this technique is valid only for this particular application.

Table 5.1 Summary of Process Reaction Curve Method

Characteristics	Process Reaction Curve
Experiment duration	The process should reach steady state
Input change	A nearly perfect step change is required
Model structure	The model is restricted to first order with dead time
Accuracy with unmeasured disturbances	Accuracy can be strongly affected (degraded) by significant disturbances
Diagnostic	Plot model versus data; return input to initial value
Calculations	Simple hand and graphical calculations

There are several choices in order to perform the intelligent technique using the System Identification Toolbox. There are two commonly used models for this type of project, which are the ARX and ARMAX models.

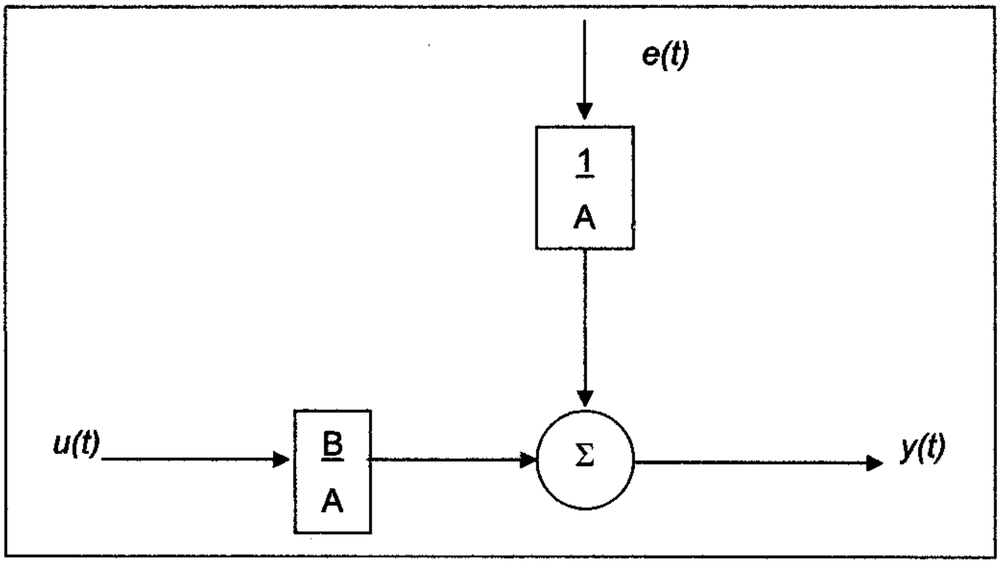

Figure 5.17 ARX model structure

ARX model has two parameters which are A and B. the order of this model is heavily depend on the power of both parameters, which means that ARX model has the ability to describe a system with a disturbance. In the System Identification Toolbox, the parameters of the ARX model structure $A(q)y(t) = B(q)u(t-nk) + e(t)$ are intelligently estimated by the software using the least square method. The author only needs to define the orders and delay ([*na nb nk*]) of the ARX model. *na* is the number of poles of the system, *nb* is the number of zeros and *nk* is the delay.

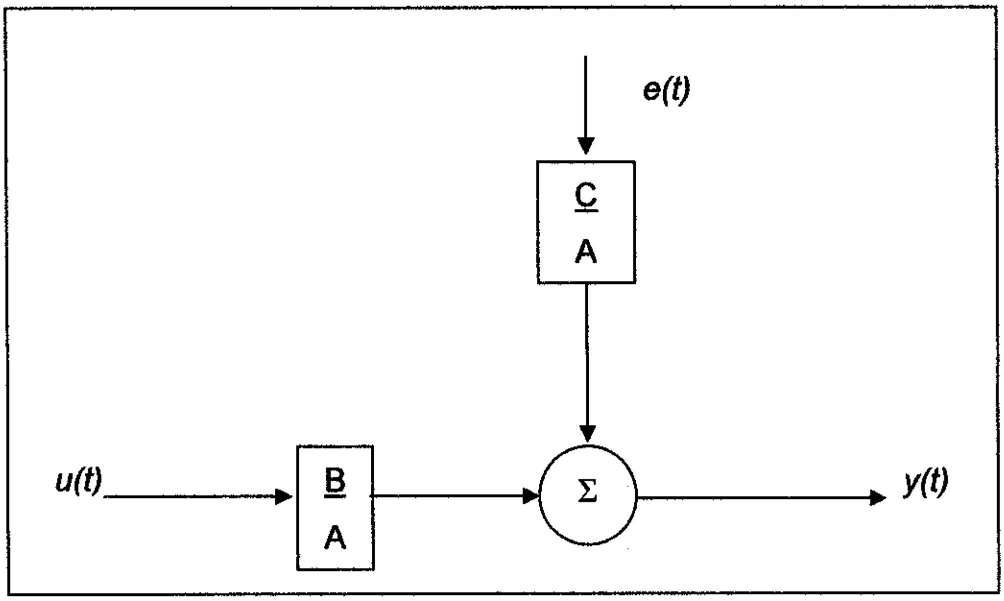

Figure 5.18 ARMAX model structure

The ARMAX model structure parameters $A(q)y(t) = B(q)u(t-nk) + C(q)e(t)$ are estimated using a prediction error method. Same as the ARX model, ARMAX model needs the author to specify the order of the models. ARMAX has one additional element which is *nc*, that represents the number of zeros for the noise transfer function.

The flexibility of describing the equation error for ARMAX model is improved as a moving average of white noise is added. This is because ARMAX has more parameter compared to the ARX model. Having three parameters gives advantage to the ARMAX model to describe better than ARX model. With this capability, ARMAX model are more reliable and therefore this will gill the advantage for ARMAX model to describe a higher order model with a significant amount of noise or disturbance better.

CHAPTER 6
CONCLUSION & RECOMMENDATION

6.1 Conclusion

System Identification is a method for generating workable dynamic response models based on observed datasets from an actual system. The modeling process is based on the observed input and output data of a system. The objective of this project is to design and implement System Identification techniques for a Liquid System Pilot Plant. The project will also make comparison between the conventional and System Identification modeling techniques.

From analysis, empirical modeling produced a linear transfer function, which is adequate for the project implementation. For the intelligent technique, two model predictors (ARX and ARMAX) are used to obtain the best model. From the analysis, it shows that the ARX models exhibit quite the same characteristics as the models obtained from the empirical technique. By using the System Identification Toolbox, the ARMAX structures are the best models in representing the actual system apart from the other models obtained from the empirical technique and ARX structures.

After model validation tests, all models from both the conventional and intelligent technique are capable of reproducing observed data with minimum predictor error. From the validation test also, it can be said that the model that best represent the actual system is the ARMAX model of order 2 since it gives the lowest steady-state and model errors. Hence, it is concluded that the objective of the project have successfully met by proving that the intelligent method by means of System Identification Toolbox achieved a better performance compared to the conventional technique.

6.2 Recommendation

System Identification is a powerful tool for real plant process modeling. Therefore, having the knowledge of deducing a mathematical model by studying the behavior of input and output data will be helpful in a process control. This project can be further improved by the examination and implementation of other intelligent modeling approaches which could better represent the real system.

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[3] Gene F. Franklin, J. David Powell and Abbas Emami-Naeini, *Feedback Control of Dynamics Systems*, 4th Edition, Prentice Hall, New Jersey (2002)

[4] Thomas E. Marlin, *Process Control: Designing Processes and Control Systems for Dynamic Performance*, 2nd Edition, Mc Graw Hill, New York (2000)

[5] Charles L. Phillips and H. Troy Nagle, *Digital Control System Analysis and Design,* 3rd Edition, Prentice Hall, New Jersey (1995)

APPENDICES

APPENDIX I: The actual dataset

APPENDIX II: The actual plot for the experiment

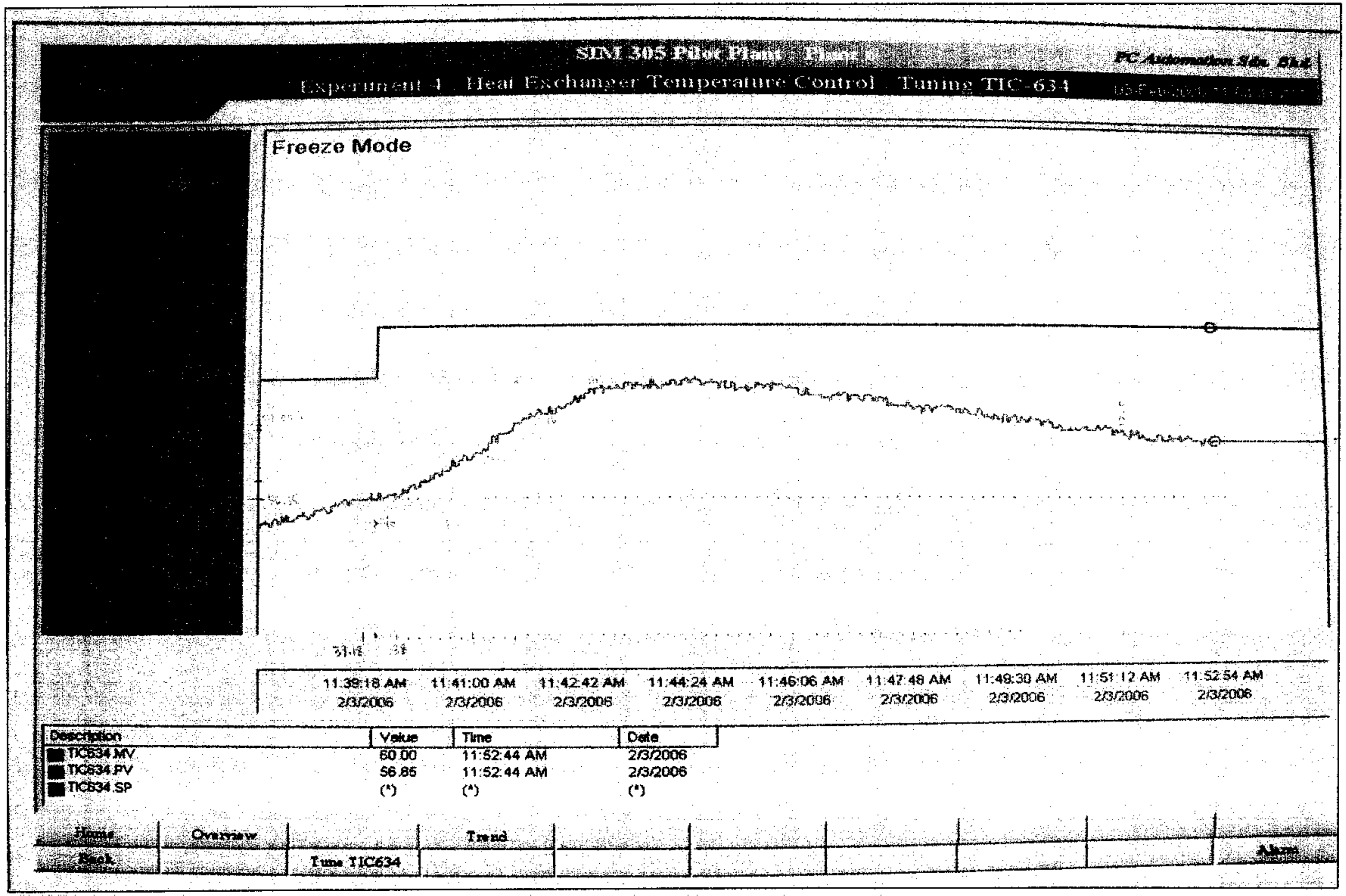
APPENDIX III: The P&ID for the Pilot Plant 6 (Heat Exchanger Temperature Control)

APPENDIX I

Time	Input (%)	Output (oC)
11.39.18	50	56.35
11.39.28	60	56.35
11.39.38	60	56.35
11.39.49	60	56.43
11.39.59	60	56.45
11.40.09	60	56.50
11.40.19	60	56.55
11.40.29	60	56.60
11.40.40	60	56.65
11.40.50	60	56.70
11.41.00	60	56.70
11.41.10	60	56.80
11.41.20	60	56.90
11.41.31	60	56.95
11.41.41	60	57.05
11.41.51	60	57.10
11.42.01	60	57.15
11.42.11	60	57.15
11.42.22	60	57.18
11.42.32	60	57.23
11.42.42	60	57.30
11.42.52	60	57.35
11.43.02	60	57.38
11.43.13	60	57.38
11.43.23	60	57.40
11.43.33	60	57.40
11.43.43	60	57.40
11.43.53	60	57.38
11.44.04	60	57.40
11.44.14	60	57.43
11.44.24	60	57.45
11.44.34	60	57.43
11.44.44	60	57.45
11.44.55	60	57.43
11.45.05	60	57.40
11.45.15	60	57.38
11.45.25	60	57.38
11.45.35	60	57.40
11.45.46	60	57.43
11.45.56	60	57.40

Time	Input (%)	Output (oC)
11.46.06	60	57.33
11.46.16	60	57.33
11.46.26	60	57.33
11.46.37	60	57.28
11.46.47	60	57.33
11.46.57	60	57.30
11.47.07	60	57.28
11.47.17	60	57.28
11.47.28	60	57.28
11.47.38	60	57.23
11.47.48	60	57.23
11.47.58	60	57.20
11.48.08	60	57.20
11.48.19	60	57.20
11.48.29	60	57.20
11.48.39	60	57.18
11.48.49	60	57.15
11.48.59	60	57.18
11.49.10	60	57.13
11.49.20	60	57.10
11.49.30	60	57.10
11.49.40	60	57.08
11.49.50	60	57.08
11.50.01	60	57.05
11.50.11	60	57.03
11.50.21	60	57.00
11.50.31	60	57.00
11.50.41	60	57.00
11.50.52	60	57.00
11.51.02	60	56.98
11.51.12	60	56.98
11.51.22	60	56.95
11.51.32	60	56.93
11.51.43	60	56.90
11.51.53	60	56.90
11.52.03	60	56.90
11.52.13	60	56.90
11.52.23	60	56.90
11.52.34	60	56.90
11.52.44	60	56.90
11.52.54	60	56.90

APPENDIX II


SIM 305 Pilot Plant
PC Automation Sdn. Bhd.
Experiment 4 . Heat Exchanger Temperature Control . Tuning TIC-634
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Description | Value | Time | Date
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TIC634.PV | 56.85 | 11:52:44 AM | 2/3/2006
TIC634.SP | (*) | (*) | (*)
Home
Back
Overview
Tune TIC634
Trend
Alarm

APPENDIX III