CHAPTER 1 INTRODUCTION

1.1 Background of Study

The project is about to study on statistical model for defect count for control system. By definition, statistical model also known as the science of making effective use of numerical data relating to groups of individuals or experiments. It deals with all aspects of this, including not only the collection, analysis and interpretation of such data, but also the planning of the collection of data, in terms of the design of surveys and experiments [1]. In another definition, statistical model is defined as the mathematics of the collection, organization, and interpretation of numerical data, especially the analysis of population characteristics by inference from sampling [2]. By meaning, the defect count can be defined as a lack of something necessary for completeness or perfection; shortcoming; deficiency [3].

In a dept understanding of the project title, the project is actually to apply the statistical technique to evaluate the performance of the process flow in Flow Ratio Control Tuning plant for control system in Universiti Teknologi PETRONAS process plant control laboratory. The statistical model is used as a method to find the parameters value to find the transfer function in the flow ratio process plant and evaluate the errors occurs.

The plant is namely SIM305-LW1LS-X-BATCH (Plant 5) which is a scaleddown liquid phase Level Process Pilot Plant. It is a self contained unit designed to simulate real liquid level-flow process found in industry plants. The plant consists of two raw material tanks, VE-510 and VE-520 that provides two separate flow streams of water to product tank, VE-530. The flow from VE-510 is pumped using P-511 while the flow from VE-520 is pumped using P-521. Water is then collected in VE-530 before it is returned to the raw material tanks HV-530 and HV-53. The schematic of the plant is shown in Appendix. This experiment is using the flow ratio control setup where the ratio of 2 flow streams is balanced in order to produce a specified output.

Flow ratio control is commonly used in plant operation where constant ratio has to be maintained between two or more process ingredients. Such situations can be seen in solvent blending into base material and fuel-to-air ratio for efficient combustion in a burner of furnace, among others. Flow rate is manipulated in ratio control since the variable has negligible dynamics; practically no dead time and very little amount of lead or lag control required.

1.2 Problem Statement

In the plant control process, there is always occurs an errors or defect in the control variable. In fine tuning, the output which also known as the control variable (CV) must response faster due to the change of the input or the set point (SP). The good response should be fast enough in order to maintain CV according to the SP. This fast response can be achieved by controlling the manipulated variable (MV) in the process. However, the errors can occurred in tuning the MV due to mistakes in calculating MV parameters.

In plant process control plant, an Empirical modeling is a commonly technique in tuning the manipulated variable to get the parameters. The empirical model technique which applies simple calculation by getting the immediate data from Process Reaction Curve (PRC) has always giving errors in parameters values. Therefore, the statistical modeling is an alternative approach which gives more accurate value compare to the empirical modeling parameters.

In this Final year project II, the analysis of the data that were collected in previous Final Year project 1 is done. The transfer function of the plant is calculated using statistical model identification approach. Two main approaches in statistical modeling that were used are Regression Analysis and The least Squares method. Both approaches are performed to find the parameter values of plant transfer function.

1.3 Objectives and Scope of Study

There are some objectives to be achieved in this final year project which are as follows:

- 1. Analysis of the data to find plant transfer function parameters.
- 2. Evaluate the Data from the experiment using Least Squares Method and Regression Analysis.
- 3. Compare the Empirical Modeling and Statistical Modeling Approach.

CHAPTER 2

LITERATURE REVIEW

2.1 Concept of Statistical Modeling

2.1.1 Definition of Statistical

Statistics is the science of making effective use of numerical data relating to groups of individuals or experiments. It deals with all aspects of this, including not only the collection, analysis and interpretation of such data, but also the planning of the collection of data, in terms of the design of surveys and experiments.

A statistician is someone who is particularly versed in the ways of thinking necessary for the successful application of statistical analysis. Often such people have gained this experience after starting work in any of a number of fields. There is also a discipline called mathematical statistics, which is concerned with the theoretical basis of the subject.

The word statistics can either be singular or plural. When it refers to the discipline, "statistics" is singular, as in "Statistics is an art." When it refers to quantities (such as mean and median) calculated from a set of data, statistics is plural, as in "These statistics are misleading." [4]

2.1.2 Overview on Statistical

In applying statistics to a scientific, industrial, or societal problem, it is necessary to begin with a population or process to be studied. Populations can be diverse topics such as "all persons living in a country" or "every atom composing a crystal". A population can also be composed of observations of a process at various times, with the data from each observation serving as a different member of the overall group. Data collected about this kind of "population" constitutes what is called a time series.

For practical reasons, a chosen subset of the population called a sample is studied — as opposed to compiling data about the entire group (an operation called census). Once a sample that is representative of the population is determined, data is collected for the sample members in an observational or experimental setting. This data can then be subjected to statistical analysis, serving two related purposes: description and inference.

The concept of correlation is particularly noteworthy for the potential confusion it can cause. Statistical analysis of a data set often reveals that two variables (properties) of the population under consideration tend to vary together, as if they are connected. For example, a study of annual income that also looks at age of death might find that poor people tend to have shorter lives than affluent people. The two variables are said to be correlated; however, they may or may not be the cause of one another. The correlation phenomena could be caused by a third, previously unconsidered phenomenon, called a lurking variable or confounding variable. For this reason, there is no way to immediately infer the existence of a causal relationship between the two variables. [4]

For a sample to be used as a guide to an entire population, it is important that it is truly a representative of that overall population. Representative sampling assured, inferences and conclusions can be safely extended from the sample to the population as a whole. A major problem lies in determining the extent to which the sample chosen is actually representative. Statistics offers methods to estimate and correct for any random trending within the sample and data collection procedures. There are also methods for designing experiments that can lessen these issues at the outset of a study, strengthening its capability to discern truths about the population. Statisticians describe stronger methods as more "robust".

The fundamental mathematical concept employed in understanding potential randomness is probability. Mathematical statistics (also called statistical theory) is the branch of applied mathematics that uses probability theory and analysis to examine the theoretical basis of statistics. The use of any statistical method is valid only when the system or population under consideration satisfies the basic mathematical assumptions of the method. [4]

2.1.3 Scope of Study

Statistics is considered by some to be a mathematical science pertaining to the collection, analysis, interpretation or explanation, and presentation of data, while others consider it to be a branch of mathematics concerned with collecting and interpreting data. Because of its empirical roots and its focus on applications, statistics is usually considered to be a distinct mathematical science rather than a branch of mathematics.

Statisticians improve the quality of data with the design of experiments and survey sampling. Statistics also provides tools for prediction and forecasting using data and statistical models. Statistics is applicable to a wide variety of academic disciplines, including natural and social sciences, government, and business.

Statistical methods can be used to summarize or describe a collection of data; this is called descriptive statistics. This is useful in research, when communicating the results of experiments. In addition, patterns in the data may be modeled in a way that accounts for randomness and uncertainty in the observations, and are then used to draw inferences about the process or population being studied; this is called inferential statistics. Inference is a vital element of scientific advance, since it provides a prediction (based in data) for where a theory logically leads. To further prove the guiding theory, these predictions are tested as well, as part of the scientific method. If the inference holds true, then the descriptive statistics of the new data increase the soundness of that hypothesis. Descriptive statistics and inferential statistics (a.k.a., predictive statistics) together comprise applied statistics. [4]

2.1.4 History of Statistical

Some scholars pinpoint the origin of statistics to 1663, with the publication of Natural and Political Observations upon the Bills of Mortality by John Graunt. Early applications of statistical thinking revolved around the needs of states to base policy on demographic and economic data, hence its stat- etymology. The scope of the discipline of statistics broadened in the early 19th century to include the collection and analysis of data in general. Today, statistics is widely employed in government, business, and the natural and social sciences.

Its mathematical foundations were laid in the 17th century with the development of probability theory by Blaise Pascal and Pierre de Fermat. Probability theory arose from the study of games of chance. The method of least squares was first described by Carl Friedrich Gauss around 1794. The use of modern computers has expedited large-scale statistical computation, and has also made possible new methods that are impractical to perform manually. [4]

2.2 Statistical Modeling in Plant Process Control System

The purpose of Statistical Modeling is to evaluate the relationship of variables involved between input and output. In this project, we will study the connectivity of input and output variable in order to understand its behavior and thus improve the system performance. Some of the important general inputs need to be considered in control process plant are:

- 1) Process Flow
- 2) Temperature
- 3) Pressure
- 4) Flow ratio

By evaluating the performance, we will then study on the defect occurs and try to eliminate them by using statistical approach. Therefore, selecting the best variables or inputs and to determine on relative impact on system performance is very important. In solving this problem, mathematical simulation tools and statistical model are employed to construct an appropriate regression models able to predict system behavior when multiple input multiple output (MIMO) or single input single output (SISO) system are involved. As the result, we will study and focus on the defect or failure result in the final system behavior. The efficiency of the gain is depends on the controlling process which involved several dominant variables in order to maximize the productivity. Due to this, defect can be count or identified by observing the output behavior. Using a mathematical approach such as statistical model we can use the previous data in order to manipulate the process by controlling input and output variable using some calculation and simulation. Thus, we can also work to eliminate the errors to improve the production process as well to improve and optimize the process.

In plant process control, the controlling process is depends on the Manipulated Variable (MV). There are several parameters for controlling the flow ratio MVs which are the value of Ku, Pu, Kc, Ti, Td. Using this parameters value, we will calculated and tuning the CV until the system is stable enough or reaching the set point. The values can be calculated by using two methods which are empirical modeling (instant values) and statistical modeling (collecting data approach). By using these parameters values, we will then do the fine tuning using Proportional Integral Derivative approach to evaluate the system performance due to the input changes. The expected output, CV is targeted to achieve zero offset which means reaching its set point (SP).

2.3 Comparison between Statistical and Empirical Modeling

For my project, I have done research on empirical model and statistical model. These models are the most common type used in control process plan to evaluate the performance of the input output relationship. There are several step involved in both model in order to find the transfer function. However, empirical model are limited to first order with dead time only whereas statistical model has these advantages compare to the empirical model which are:

- Introduce a 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. It is not necessary that the process regain steady state at the end of the experiment.
- Calculate the model parameters using least square method, which minimizes the sum of error squared between the measured and predicted values over all samples.

2.4 Example of Output Response

Examples of the input output relationship are shown in figures below [6]:

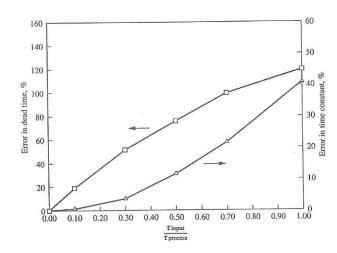


Figure 1: Sensitivity of process reaction curve to an imperfect step input.

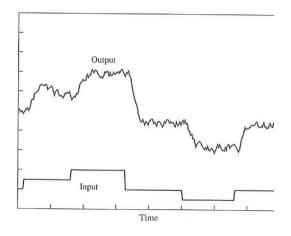


Figure 2: example of experimental design to evaluate the linearity of the process.

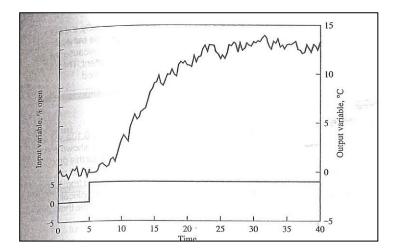


Figure 3: Process reaction curve identification

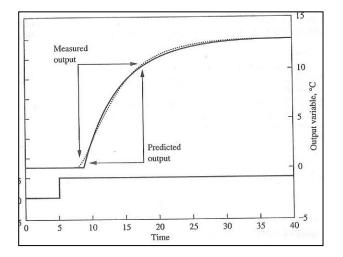


Figure 4: Comparison of measured and predicted output.

CHAPTER 3

THE METHODOLOGY

3.1 Procedure Identification

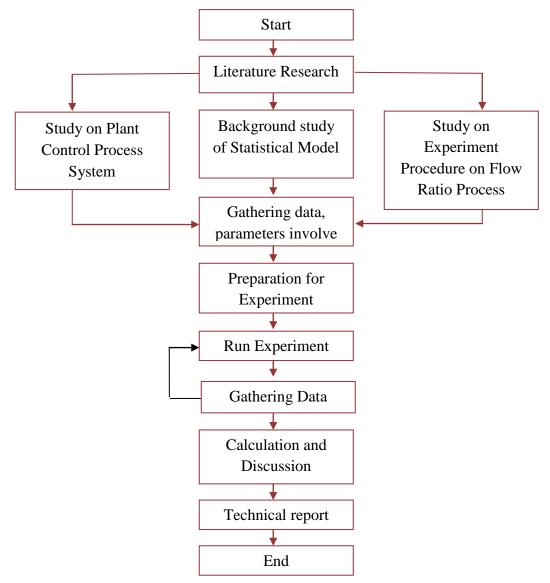


Figure 5: Flowchart of the project

3.2 Empirical Modeling

It is a modeling method specifically designs for process control which more preferable called empirical identification. The model developed using this method provide the dynamic relationship between selected input and output variables. In empirical model building, models are determined by making small changes in the input variable(s) about a nominal operating condition. This model involves designed experiments, during which the process is perturbed to generate dynamic data. The model can be achieve by two identification method which are process reaction curve and employ sample, and employs statistical principles for determining the parameters. [5]

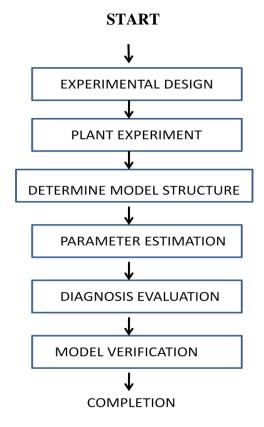


Figure 6: The Flow Step to Perform Statistical and Empirical Modeling

In Empirical Modeling, Process Reaction Curve is performed in order to find the transfer function of the plant. There are two methods to find the transfer function which are method 1 and method 2. In method 1, maximum slope is needed to find the time constant, T while in method 2, the time at 28% and 63% is taken to find the time constant and dead time.

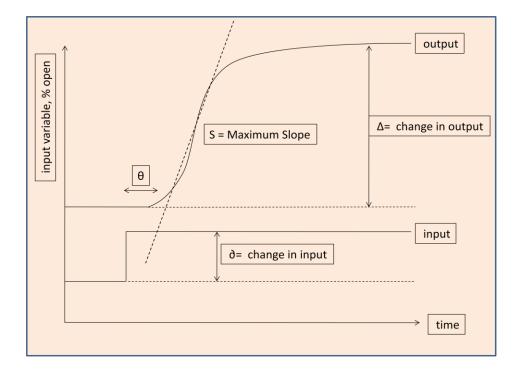


Figure 7: Process Reaction Curve in empirical modeling, method 1

$$Kp = \frac{\Delta}{\partial};$$

T(time constant) = $\frac{\Delta}{s}$

 θ = shown in the graph

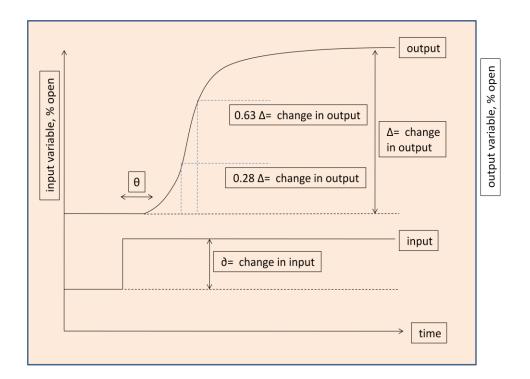


Figure 8: Process Reaction Curve in empirical modeling, method 2

$$Kp = \frac{\Delta}{\partial};$$

T(time constant) = 1.5[t(63%) - t(28%)]

$$\theta = t(63\%) - T(time \text{ constant})$$

3.3 Statistical Model Identification

The statistical identification method provides more flexible approaches to identification that relax this limits to model structure and experimental design. In addition, the statistical method uses all data and not just a few points from the response, which provide better parameter estimates. The transfer function model must be converted into and algebraic model that relates the current value of the output to past values of the input to output. Z-transform would be the most accurate for linear system, which serve a similar purpose for discrete systems as Laplace transform serve for continuous system. [5]

The first order dead time model can be written in the time domain according to the equation:

$$T_{\frac{dY'(t)}{dt}}^{\frac{dY'(t)}{dt}} + Y'(t) = KpX'(t-\theta).....(1)$$

The prime denotes deviation from the initial steady state value. This differential equation can be integrated from time (t1) to (t1 + Δ t) assuming the input X'(t) is constant over period. The dead time is represented as sample delays, ($\Gamma = \theta + \Delta$ t). Then the equation will become:

$$Y'(i+1) = e^{-\Delta t/t}Y'i + Kp(1-e^{-\frac{\Delta t}{t}})X'(i-\Gamma).....(2)$$

To be simple, this equation can be simplified as:

$$Y'(i+1) = aY'i + bX'(i - \Gamma).....(3)$$

Which, $a = e^{-\Delta t/t}$, and

$$\mathsf{b} = Kp(1 - e^{-\frac{\Delta \mathsf{t}}{\mathsf{t}}})$$

From this equation, the challenge is to find the parameters which are a, b, and Γ that provide the best model for the data. Thus, the model parameters Kp, t and θ can be calculated. [5]

Table 1: Data for Statistical Mode	el Identification
------------------------------------	-------------------

Data for statistical model identification							
data in original format as collected in experiment				data in restructured format for regression model fitting			
time, t	input, X	output, Y	sample no. i	output, Y'(i +1)	output, Y'(i)	Delayed input, X'(i-2)	
0	50	75	1				
0.2	50	75	2				
0.4	52	75	3	0	0	0	
0.6	52	75	4	0.05	0	0	
0.8	52	75.05	5	0.1	0.05	2	
1	52	75.1	6	0.3	0.1	2	
1.2	52	75.3	7	0.6	0.3	2	
1.4	52	75.6	8	0.7	0.6	2	
1.6	52	75.7					

Using the model, it is possible to predict the output variable at any time with, (Y'i+1)p represent the predicted value, using this equation:

$$Y'(i+1) predicted = \mathbf{a}Y'i(measured) + \mathbf{b}X'(i-\Gamma)(measured).....(4)$$

The error can be express as:

$$\sum_{i=\Gamma+1}^{n} [Y'(i+1)m - Y'(i+1)p]^{2}].....(5)$$

The minimization of this term requires that the derivatives of the sum of error square with respect to parameters are zero.

$$\frac{\partial}{\partial a} \sum_{i=\Gamma+1}^{n} \operatorname{Ei}^{2} = -2 \sum_{i=\Gamma+1}^{n} \operatorname{Y}^{i}(m) [Y^{'}(i+1)m - Y^{'}(i+1)p]^{2}] = 0$$

$$\frac{\partial}{\partial b} \sum_{i=\Gamma+1}^{n} \operatorname{Ei}^{2} = -2 \sum_{i=\Gamma+1}^{n} \operatorname{X}^{i}(i-\Gamma)m [Y^{'}(i+1)m - Y^{'}(i+1)p]^{2}] = 0$$

$$U = \frac{Y'3}{Y'4} \frac{X^{'}3 - \Gamma}{X'4 - \Gamma}$$

$$U = \frac{Y'4}{Y'n - 1} \frac{X'3 - \Gamma}{X'n - \Gamma - 1}$$

$$Z = \frac{Y'4}{Y'5} \frac{Y'4}{Y'n}$$
[a b] = inv (U'*U)*U'*Z
Where,

U' = U Transpose Matrix

This method can be use in determining the coefficient a and b. To determine the dead time accurately, it is necessary to solve the Least Square problem for several values of Γ , with Γ giving the lowest sum of error squared. This least square problem is solved using MATLAB software.

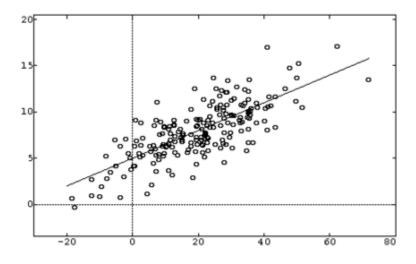


Figure 9: Linear Regression line

Linear regression models are often fitted using the least squares approach, but they may also be fitted in other ways, such as by minimizing the "lack of fit" in some other norm, or by minimizing a penalized version of the least squares loss function as in ridge regression. [7] By using linear regression, we can analyze the residuals or errors in the data.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Experiment Data and PID Tuning



4.1.1 Experimental Data

Figure 10: Process Reaction Curve (PRC) for flow ratio empirical modeling

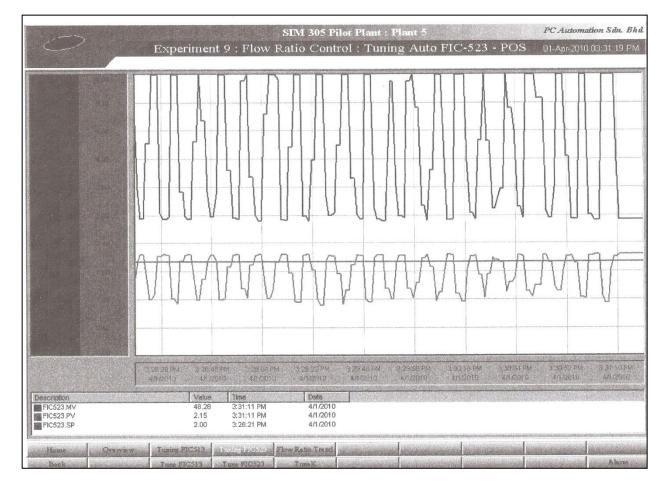


Figure 11: Tuning parameter Pu

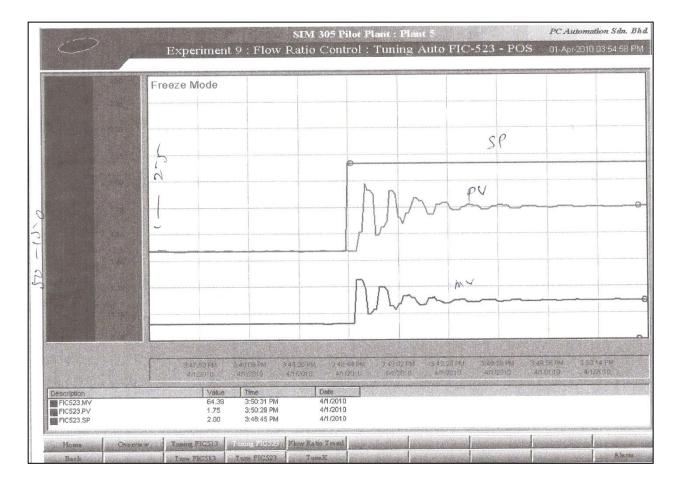


Figure 12: Tuning parameters Ku and Pu

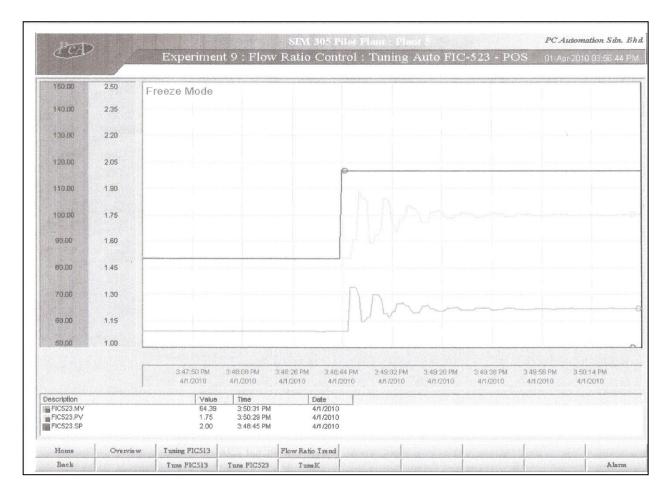


Figure 13: Tuning parameter Kc

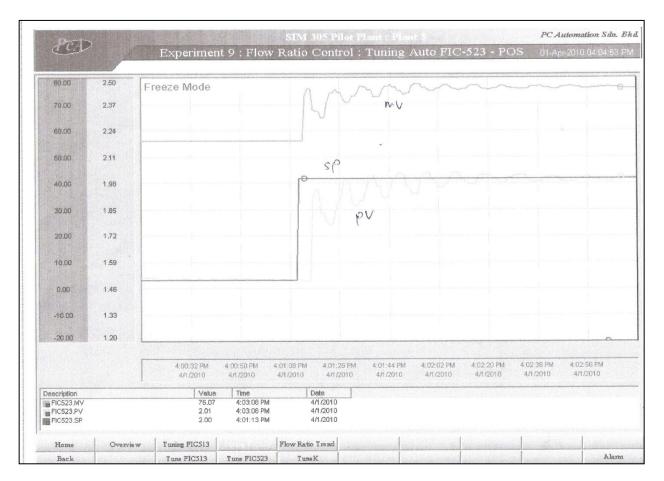


Figure 14: Controller Performance Proportional- Integral (PI)

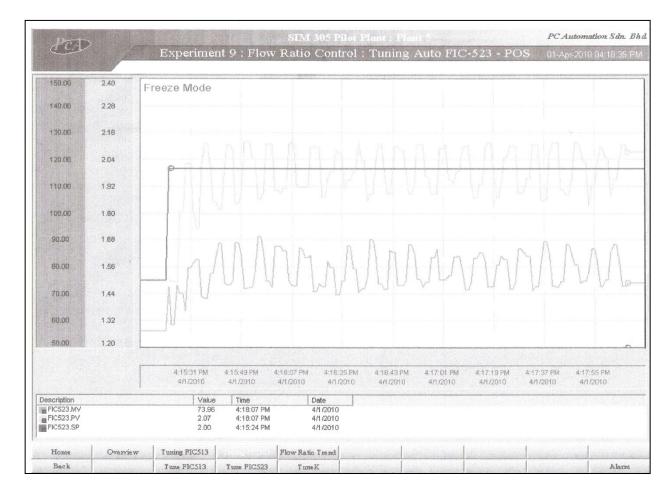


Figure 15: Controller Performance Proportional-Integral-Derivative (PID)

Measurement	Exp1	Exp2	Exp3
Ultimate Gain, Ku	2	1.8	2.0
Time for 3 oscillation	0.433 min	0.4333 min	0.3833 min
periods			
Calculation	value	value	value
Ultimate Time, Pu	0.144 min	0.145 min	0.128 min
(Time for 1 oscillation			
Period)			

Table 2: Results For Closed- Loop Tuning (Ultimate Sensitivity Test for FIC-523 Secondary loop)

In the experiment, the first step is to find the parameters value using Ultimate Sensitivity Test. Several experiments has been done to find the best parameters value in ultimate sensitivity test in order to perform find tuning using proportional integral derivative, P&ID controller. The parameter value in ultimate sensitivity test for secondary loop are calculated and listed in the table 1.

Table 3: P&ID Controller Parameters C

Tuning Parameters		P-only			PI			PID	
Model	Exp1	Exp2	Exp3	Exp1	Exp2	Exp3	Exp1	Exp2	Exp3
Proportional	0.9	0.9	1	0.82	0.81	0.90	1.03	1.08	1.20
Gain, Kc									
Integral	-			7.23	7.25	6.40	4.30	4.35	3.85
Time, Ti									
Derivative	-			-			1.08	1.09	0.96
Time, Td									

The P&ID controller for FIC-523 are calculated using Ziegler-Nichols Closed Loop Correlation. The parameter value for P&ID controller are calculated and listed in table 2. Table 4: Result for Closed loop Tuning

Measurement	Exp1	Exp2	Exp3
Ultimate Gain, Ku	17	16	15
Time for 3 oscillation	37s	36s	34s
Periods			
Ultimate Time, Pu	12.33s	12s	8.3s

Secondly, the parameter values for the FIC-513 primary loop are done using ultimate sensitivity test. The parameter value is calculated and listed in table 3.

Table 5: PID controller Parameters C (Ultimate Sensitivity Test for Primary Loop)

Tuning Parameters		P-only			PI			PID	
Model	Exp1	Exp2	Exp3	Exp1	Exp2	Exp3	Exp1	Exp2	Exp3
Proportional	9	8	1.2	7.3	7.2	10.7	9.7	9.6	14.4
Gain, Kc									
Integral	-			11	10	6.8	6.2	6	4.15
Time, Ti									
Derivative	-			_			1.6	1.5	1.04
Time, Td									

The P&ID controller FIC-513 are calculated using Ziegler-Nichols Closed Loop Correlation. The parameter value for P&ID controller are calculated and listed in table 2.

4.1.2 FIC-523 (Secondary Loop)

Performance	P-only			PI			PID		
Measure									
Model	Exp1	Exp2	Exp3	Exp1	Exp2	Exp3	Exp1	Exp2	Exp3
Offset	0.280	0.284		0					
Decay Ratio	0.526	0.571	0.6	0.55	0.5	0.75	0.78	0.75	-
Rise Time	-		0.24	9.47s	9.47	18	4.70s	4.74	
Settling	45.65	49.7	36	120.0s	111.31	65	-		
Time									
MV	0.947	0.957	0.885	0.087	0.088	0.078	-		
Overshoot									
Maximum	0.127	0.126	0.120	0.036	0.036	0.028	0.14	0.13	0.14
CV									
derivation									

Table 6: Control Loop for Performance Test of Secondary Loop (FIC 523)

P –only Controller

Using P controller, PV is not reach the set point. Results shows PV is an under damped system. The decay ratio is too high and it is not suitable for this process. The manipulated variable (MV) is not change large enough from its previous peak value. PV never reach the set point, therefore the rise time cannot be calculated. The settling time is short and MV overshoot is quite high. The maximum CV deviation is high.

PI Controller

PV is reached the set point and reaches steady state. From the observation, PV is over damped system with little oscillation. The decay ratio is high but it is acceptable. Rise time is fast but settling time is long because it is to reach steady state. Both MV overshoots and maximum CV deviation is low.

PID Controller

Offset is very high but it cannot be calculated because there is no steady state value. The decay ratio is high. The rise time is short but no settling time since the system did not reach steady state. From the result, both MV overshoots and maximum CV deviation is high. The system is an unstable system because cannot reach the steady state.

4.1.3 FIC-513 (Primary Loop)

Performance Measure	P-only			PI			PID		
Model	Exp1	Exp2	Exp3	Exp1	Exp2	Exp3	Exp1	Exp2	Exp3
Offset	0.350	0.356		0	0		-		
Decay Ratio	0.501	0.522		1.24	1.25		0.621	0.622	0.5
Rise Time	-			87.10s	87.14		22.8s	22.7	
Settling	0.350	0.355		-		8.6	0.054	0.054	7
Time									
MV	-			250	250	6.9	-		5.7
Overshoot									
Maximum	0.138	0.138		0.03	0.03		0.050	0.054	
CV									
derivation									

Table 7: Control loop Performance Test of Primary Loop (FIC513)

P only

PV is not reached the set point and it also not reached the steady state. Since it is not reached the set point, therefore there is no rise time. It is also not have settling time because it is not reached steady state. Offset and maximum deviation is not accurate. The system is undamped and marginally stable.

PI Controller

PV is reached the set point with no offset and it reached steady state. The decay ratio is accepted. The rise time and settling time has quite long period. It is also has no MV overshoot because the secondary loop is added. The maximum CV deviation is very low. The system is an overdamped system.

PID controller

PV is reached the SP but it is not reached steady state. Therefore, offset and settling time cannot be calculated. The decay ratio is accepted. The rise time is very short. Both MV overshoot and maximum deviation is very low.

4.2 Statistical Model Identification

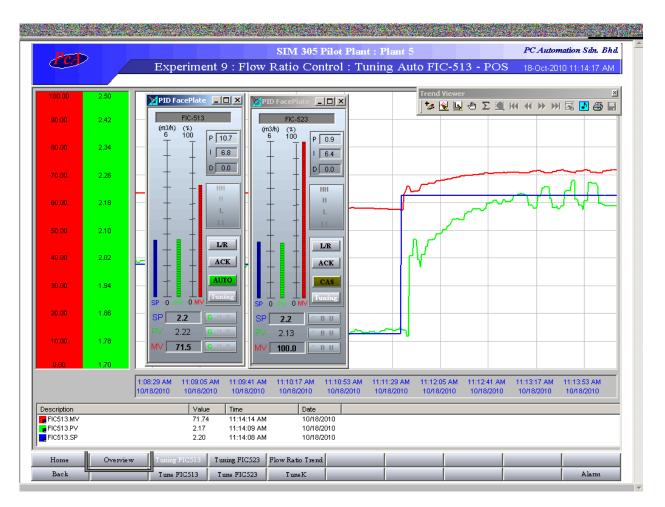


Figure 16: Process Reaction Curve for Cascade Mode (SP 1.8-2.2)

Table 8: PI controller Experiment 3

	Р	Ι
Primary Loop	10.7	6.8
Secondary Loop	0.9	6.4

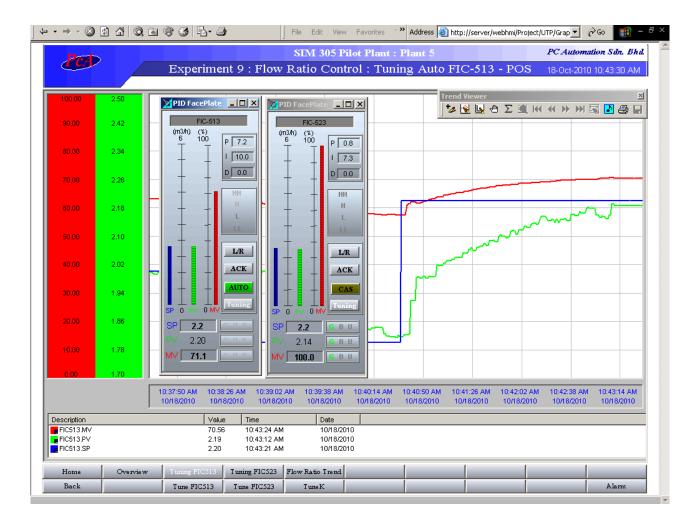


Figure 17: Process Reaction Curve for Cascade Mode (SP 1.8-2.2)

Table 9: PI controller Experiment 2	Table 9:	PI controller	Experiment 2
-------------------------------------	----------	---------------	--------------

	Р	Ι
Primary Loop	7.2	10
Secondary Loop	0.8	7.3

	time,		output,	output,	output,Y'i	Delayed input,	
Sample no. i	t	input,Xi	Υ	Y'(i+1) m	m	X'(i-2) m	input,X'i
1	0	1.8	13.33	0	0		0
2	12	1.8	13.33	0	0		0
3	24	1.8	13.33	1.67	0	0	0
4	36	1.8	15	26.67	1.67	0	0
5	48	2.2	40	26.67	26.67	0	0.4
6	60	2.2	40	36.67	26.67	0	0.4
7	72	2.2	50	40	36.67	0.4	0.4
8	84	2.2	53.33	43.33	40	0.4	0.4
9	96	2.2	56.66	46.67	43.33	0.4	0.4
10	108	2.2	60	46.67	46.67	0.4	0.4
11	120	2.2	60	50	46.67	0.4	0.4
12	132	2.2	63.33	50	50	0.4	0.4
13	144	2.2	63.33	44.995	50	0.4	0.4
14	156	2.2	58.325	51.665	44.995	0.4	0.4
15	168	2.2	64.995	46.67	51.665	0.4	0.4
16	180	2.2	60	46.67	46.67	0.4	0.4
17	192	2.2	60	51.665	46.67	0.4	0.4
18	204	2.2	64.995	46.67	51.665	0.4	0.4
19	216	2.2	60	46.67	46.67	0.4	0.4
20	228	2.2	60	46.67	46.67	0.4	0.4
21	240	2.2	60	46.67	46.67	0.4	0.4
22	252	2.2	60	46.67	46.67	0.4	0.4
23	264	2.2	60				

Table 10: Statistical Model Identification table from experiment 3

The data from Process Reaction Curve for cascade mode are use in statistical model identification. The Set Point, SP and the Process Variable, PV has been sampling and transfer to the statistical model Identification table. The predicted output and Delayed Input also have been simplified in this table.

In order to solve for the transfer function, first of all is need to calculate the parameter of a and b. The parameters are simplified using these equations:

$$U = \begin{array}{c} Y'3 & X'3 - \Gamma \\ Y'4 & X'4 - \Gamma \\ Y'n - 1 & X'n - \Gamma - 1 \end{array}$$
$$Z = \begin{array}{c} Y'4 \\ Z'5 \\ Y'n \end{array}$$
$$[a b] = inv (U'*U)*U'*Z \\Where, \\U' = U Transpose Matrix$$

inv = Inverse Matrix

Using the equation, we can find the best plant dead time, a and b. The calculation has been performed using MATLAB software.

U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0.4;40,0.4;43.33,0.4;46.67,0.4;46.67,0.4;50,0.4;50,0.4;44. 995,0.4;51.665,0.4;46.67,0.4;46.67,0.4;51.665,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

Table 11: Parameter a and b, $\theta = 2$

U =		Z =
-		
0	0	1.6700
1.6700	0	26.6700
26.6700	0	26.6700
26.6700	0	36.6700
36.6700	0.4000	40.0000
40.0000	0.4000	43.3300
43.3300	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	50.0000
50.0000	0.4000	50.0000
50.0000	0.4000	44.9950
44.9950	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
>> K=inv(U	l'*U)	>> K*U'*Z
	-,	
К =		ans =
0.0006	-0.0701	1.1011
	8.5089	-10.1496

>> U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0;40,0.4;43.33,0.4;46.67,0.4;46.67,0.4;50,0.4;50,0.4;44.99 5,0.4;51.665,0.4;46.67,0.4;46.67,0.4;51.665,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

U =	Z =
0 0	1.6700
1.6700 0	26.6700
26.6700 0	26.6700
26.6700 0	36.6700
36.6700 0	40.0000
40.0000 0.4000	43.3300
43.3300 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	50.0000
50.0000 0.4000	50.0000
50.0000 0.4000	44.9950
44.9950 0.4000	51.6650
51.6650 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	51.6650
51.6650 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
>> K=inv(U'*U)	>> K*U'*Z
К =	ans =
0.0003 -0.0405	1.1094
-0.0405 5.1794	-11.7473

Table 12: Parameter a and b, $\theta = 3$

>> U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0;40,0;43.33,0.4;46.67,0.4;46.67,0.4;50,0.4;50,0.4;50,0.4;44.995, 0.4;51.665,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

U =	Z =
0 0	1.6700
1.6700 0	26.6700
26.6700 0	26.6700
26.6700 0	36.6700
36.6700 0	40.0000
40.0000 0	43.3300
43.3300 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	50.0000
50.0000 0.4000	50.0000
50.0000 0.4000	44.9950
44.9950 0.4000	51.6650
51.6650 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	51.6650
51.6650 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
>> K=inv(U'*U)	>> K*U'*Z
К =	ans =
0.0002 -0.0267 -0.0267 3.6180	1.1062 -12.0119

Table 13: Parameter a and b, $\theta = 3$

>> U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0;40,0;43.33,0;46.67,0.4;46.67,0.4;50,0.4;50,0.4;44.995,0. 4;51.665,0.4;46.67,0.4;46.67,0.4;51.665,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

U =	Z =
0 0	1.6700
1.6700 0	26.6700
26.6700 0	26.6700
26.6700 0	36.6700
36.6700 0	40.0000
40.0000 0	43.3300
43.3300 0	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	50.0000
50.0000 0.4000	50.0000
50.0000 0.4000	44.9950
44.9950 0.4000	51.6650
51.6650 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	51.6650
51.6650 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
46.6700 0.4000	46.6700
>> K=inv(U'*U)	>> K*U'*Z
К =	ans =
0.0002 -0.0190 -0.0190 2.7477	1.1000 -11.9598

Table 14: Parameter a and b, $\theta = 5$

>> U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0;40,0;43.33,0;46.67,0;46.67,0.4;50,0.4;50,0.4;44.995,0.4; 51.665,0.4;46.67,0.4;46.67,0.4;51.665,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

U =		Z =
0	0	1.6700
1.6700	0	26.6700
26.6700	0	26.6700
26.6700	0	36.6700
36.6700	0	40.0000
40.0000	0	43.3300
43.3300	0	46.6700
46.6700	0	46.6700
46.6700	0.4000	50.0000
50.0000	0.4000	50.0000
50.0000	0.4000	44.9950
44.9950	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
>> K=inv(U	'*U)	>> K*U'*Z
К =		ans =
0.0001	-0.0141	1.0744
-0.0141	2.2128	-8.9084

Table 15: Parameter a and b, $\theta = 6$

>> U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0;40,0;43.33,0;46.67,0;46.67,0;50,0.4;50,0.4;44.995,0.4;5 1.665,0.4;46.67,0.4;46.67,0.4;51.665,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

U =		Z =
0	0	1.6700
1.6700	0	26.6700
26.6700	0	26.6700
26.6700	0	36.6700
36.6700	0	40.0000
40.0000	0	43.3300
43.3300	0	46.6700
46.6700	0	46.6700
46.6700	0	50.0000
50.0000	0.4000	50.0000
50.0000	0.4000	44.9950
44.9950	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
>> K=inv(U'	*U)	>> K*U'*Z
К =		ans =
0.0001 -	0.0113	1.0742
-0.0113	1.9210	-9.6649

Table 16: Parameter a and b, $\theta = 7$

>> U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0;40,0;43.33,0;46.67,0;46.67,0;50,0;50,0.4;44.995,0.4;51. 665,0.4;46.67,0.4;46.67,0.4;51.665,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

Table 17: Parameter a and b, $\theta = 8$

U =		Z =
0	0	1.6700
1.6700	0	26.6700
26.6700	0	26.6700
26.6700	0	36.6700
36.6700	0	40.0000
40.0000	0	43.3300
43.3300	0	46.6700
46.6700	0	46.6700
46.6700	0	50.0000
50.0000	0	50.0000
50.0000	0.4000	44.9950
44.9950	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
	** 1 1)	>> K*U'*Z
>> K=inv(U	*0)	>> K * U * Z
К =		ans =
0.0001 -0.0091	-0.0091 1.7122	1.0601 -8.0149

>> U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0;40,0;43.33,0;46.67,0;46.67,0;50,0;50,0;44.995,0.4;51.66 5,0.4;46.67,0.4;46.67,0.4;51.665,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

U =		Z =
0	0	1.6700
1.6700	0	26.6700
26.6700	0	26.6700
26.6700	0	36.6700
36.6700	0	40.0000
40.0000	0	43.3300
43.3300	0	46.6700
46.6700	0	46.6700
46.6700	0	50.0000
50.0000	0	50.0000
50.0000	0	44.9950
44.9950	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
>> K=inv(U	'*U)	>> K*U'*Z
К =		ans =
0.0001 -0.0076	-0.0076 1.5991	1.0352 -3.7244

Table 18: Parameter a and b, $\theta = 9$

>> U =

[0,0;1.67,0;26.67,0;26.67,0;36.67,0;40,0;43.33,0;46.67,0;46.67,0;50,0;50,0;44.995,0;51.665, 0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4;46.67,0.4]

>> Z =

[1.67;26.67;26.67;36.67;40;43.33;46.67;46.67;50;50;44.995;51.665;46.67;46.67;51.665;46.67;46.67;46.67;46.67;46.67]

U =		Z =
0	0	1.6700
1.6700	0	26.6700
26.6700	0	26.6700
26.6700	0	36.6700
36.6700	0	40.0000
40.0000	0	43.3300
43.3300	0	46.6700
46.6700	0	46.6700
46.6700	0	50.0000
50.0000	0	50.0000
50.0000	0	44.9950
44.9950	0	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	51.6650
51.6650	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
46.6700	0.4000	46.6700
>> K :m (1)	!*! !\	> 1/#11/# 7
>> K=inv(U	0)	>> K*U'*Z
K =		ans =
0.0001	-0.0068	1.0493
-0.0068	1.5936	-7.4614

Table 20: Parameter a and b, $\theta = 10$

Table 21: Sum of Error Squared

Dead time (Г)	а	b	Sum of Error Squared
2	1.1011	-10.1496	2.7889
3	1.1094	-11.7473	616.585
4	1.11062	-12.0119	8.529
5	1.1	-11.9598	51.375
6	1.0744	-8.9084	0.013569
7	1.0742	-9.6649	0.0156
8	1.0601	-8.0149	0.12530
9	1.0352	-3.7244	7.867
10	1.0493	-7.4614	2.8466

Table 22: Transfer Function Identification

Parameter	Value
Plant Dead Time, θ	$\Theta = (\Gamma) (\Delta t) = 6^*(12/60) = 1.2$
Time Constant, T	T = $(-\Delta t) / \ln a$ = $(-12/60)/(\ln 1.0744)$ = 2.78 min
Plant Gain, Kp	Kp = b/(1-a) = -8.9084 / (1-1.0744) = 119.7365
Transfer Function, G(s)	$G(s) = Y(s) / X(s)$ $= \frac{Kpe^{-\theta s}}{Ts+1}$ $= \frac{119e^{-1.2s}}{2.78s+1}$

4.3 Regression Analysis

Table 23: Regression Statistic

Regression Statistic		
Multiple R	0.836057	
R Square	0.698991	
Adjusted R Square	0.682269	
Standard Error	6.657232	
Observations	20	

Table 24: ANOVA

Anova					
	DS	SS	MS	F	SIGNIFICANT F
Regression	1	1852.47564	1852.47564	41.7989263	4.40873E-06
Residual	18	797.7372734	44.3187374		
Total	19	2650.212914			

Table 25: Residuals

Observation	Predicted Y	Residuals
1	22.92	-21.25
2	22.92	3.75
3	22.92	3.75
4	22.92	13.75
5	46.9803125	-6.9803125
6	46.9803125	-3.6503125
7	46.9803125	-0.3103125
8	46.9803125	-0.3103125
9	46.9803125	3.0196875
10	46.9803125	3.0196875
11	46.9803125	-1.9853125
12	46.9803125	4.6846875
13	46.9803125	-0.3103125
14	46.9803125	-0.3103125
15	46.9803125	4.6846875
16	46.9803125	-0.3103125
17	46.9803125	-0.3103125
18	46.9803125	-0.3103125
19	46.9803125	-0.3103125
20	46.9803125	-0.3103125

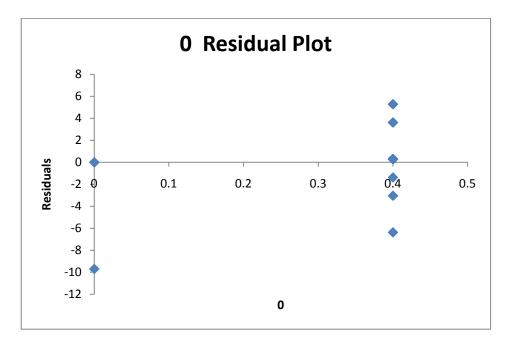


Figure 18: Residua Plot

From the simple regression analysis, we can see that there are some residuals between the input and output data. In this regression analysis, there are 20 data observation are selected. The regression analysis is performed using data analysis in Microsoft excel 2007. Because of using step input perturbation, the input is change from 0 to 0.4. The highest different is 0.4 and this can be consider as small changes in input. For the output, the change is from 13.33 to 64.995. Thus the output has higher changes than the input.

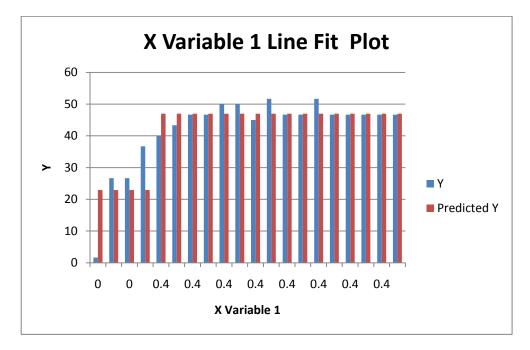


Figure 19: X Variable Line Fit Plot

From the line fit plot, we can see the different between the output and predicted output. The residuals have been listed in table 1.

4.4 Empirical Model Identification

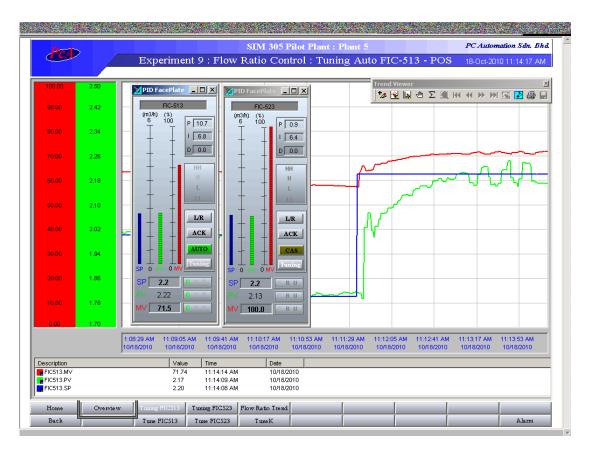


Figure 20: Cascade Mode for Empirical Modeling

Table 26: Transfer Function Identification

Parameter	Value
Plant Dead Time, θ	From the PRC, $\Theta = 6 \text{ s}$
Time Constant, T	T = 1.5 (t63% - t28%) From the PRC, $\Delta = 63.33 - 13.33 = 50$ $\Delta 63\% = 0.63*\Delta = 0.63*\Delta = 0.63*50 = 31.5$ Therefore, t63% = 42 $\Delta 26\% = 0.28*\Delta = 0.28*\Delta = 0.28*50 = 14$ Therefore, t63% = 42 T = 1.5 (42-42) = 1.5(0) = 0
Plant Gain, Kp	$Kp = \Delta/\partial$ = 50/0.4 = 125
Transfer Function, G(s)	G(s) = Y(s) / X(s) $= \frac{Kpe^{-\theta s}}{Ts+1}$ $= \frac{125e^{-6s}}{0s+1}$ $= 125e^{-6s}$

4.5 Discussion

4.5.1 P&ID Output Performance

From the experiment, we have collected the data using empirical modeling approach. There are several output responses that have been selected to test the Flow ratio performance which are the offset, decay ratio, rise time, settling time, MV overshoot and maximum CV derivation.

For the offset, zero offset is the targeted in the control variable. From this data, we can see that both primary and secondary loop has the offset in P-only mode.

For the decay ratio, smaller decay ratio should be the best in output response. From the data, the primary loop has large decay ratio in PI mode. Therefore, it shows that an error occurred to the CV due to the high MV overshoot. To have a better response, this error has to be reduced.

Besides, rise time also need to be consider in the control process. Rise time will show how fast the output response will change due to the changes in input. In order to get the good CV, Faster the response is better. From the data, the primary loop in PI mode has the highest rise time. This shows that the response is slow and it will create defect on the system performance. Slow response will effect in lagging time and increase the production cost.

4.5.2 Statistical model VS Empirical Model

From the observation of both methods, statistical modeling has given more advantages compare to the empirical model. In statistical model, there is no restriction on the shape of the perturbation to perform the modeling. Compared to empirical model, the shape of perturbation should be large enough in order to perform the method. This shows that statistical model is more flexible in the data collection compare to empirical model.

Secondly, statistical model is not necessary that the output response must regain steady state at the end of the experiment. It is enough to have 60 % of the process in order to perform the method. Compared to empirical modeling, the output response must achieved steady state in order to perform the method. For the slow output response, it may take a long period to settle down and this wills take more time to complete the process in order to analyze the data.

Besides, by having least square method in statistical model, it is minimized the sum of error squared between the measured and predicted values through all the samples. This shows that statistical model is the best way to reduce the error between the sampling data. Compared to empirical model, the error is neglected and will cause major error in the next calculation.

In the transfer function Identification, empirical method shows zero value for the time constant which is not true. Therefore, an error will occur if we taken the value into the transfer function. This can drive to wrong assumption on the process value.

CHAPTER 5

CONCLUSION AND RECOMENDATION

5.1 Conclusion

In this project, it is proven that statistical model is a useful method in analyzing the relationship between input and output. The relationship between input and output can be achieved by finding the transfer function, G(s).

$$G(s) = Y(s) / X(s)$$

The transfer function is the plant model which describes the behavior of the control system. Therefore, the error needs to be taken into account while finding the plant transfer function. Lower error means good plant model has been achieved.

In this project, statistical model has been use to find the plant transfer function. The method of statistical model is different compare to empirical modeling. The statistical method gives more accurate value compare to empirical modeling because error is not neglected. By using statistical modeling we can find and reduce the error between the input and output. This equation can be use to calculate the error:

$$\frac{\partial}{\partial a} \sum_{i=\Gamma+1}^{n} \operatorname{Ei}^{2} = -2 \sum_{i=\Gamma+1}^{n} Y'i(m) [Y'(i+1)m - Y'(i+1)p]^{2}] = 0$$
$$\frac{\partial}{\partial b} \sum_{i=\Gamma+1}^{n} \operatorname{Ei}^{2} = -2 \sum_{i=\Gamma+1}^{n} X'(i-\Gamma)m [Y'(i+1)m - Y'(i+1)p]^{2}] = 0$$

5.2 Recommendation

Considering the advantages of Statistical Model approach in plant process control system, it is recommended to use statistical approach in analyzing the data and finding the transfer function. The statistical model approach provide more flexible and utilize the data to give accurate value.

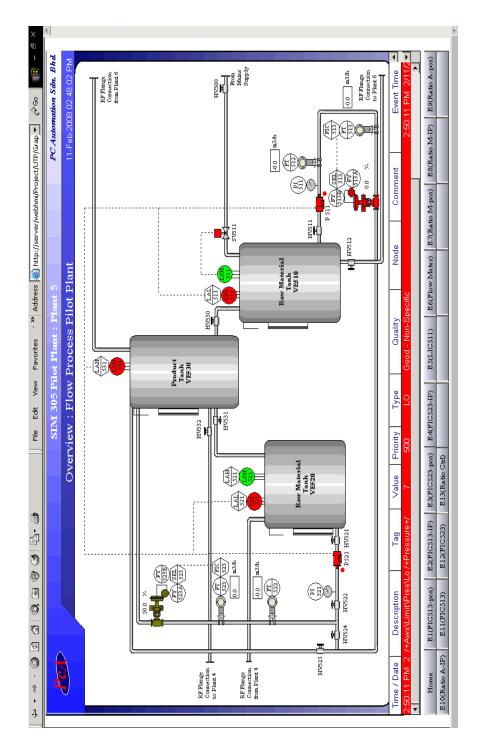
However, empirical modeling is the common technique used in evaluating the plant process nowadays. It is because empirical modeling is use simple calculation compare to the statistical modeling. Therefore, it is recommended to have programmed software of statistical model for easy calculation and evaluation. The easiest programmed software that can be use to analyze using statistical is Microsoft excel. This software provides a simple calculation such as ANOVA and Regression Analysis.

REFERENCES

- [1] http://em.wikipedia.org/wiki/statistic
- [2] http://www.thefreedictionary.com/statistics
- [3] http://www.thefreedictionary.com/statistics
- [4] http://em.wikipedia.org/wiki/statistic
- [5] STATISTICAL MODELING TECHNIQUES FOR RESERVE RANGES: A SIMULATION APPROACH Alfred Raws III, ACAS, FSA, MAAA
- [6] PLANT PROCESS CONTROL LABORATORY MANUAL
- [7] http://www.nlreg.com/intro.htm

APPENDIX

APPENDIX A: Overview of Flow Ratio Pilot Plant – SIM305-LW1LS-X-BATCH (Plant 5)



APPRENDIX B: Experiment Procedure

Section A: Preparation

Section A1

STEP	ACTION
1	Ensure that all utility Services are ready.
	-Switch on power supply to Control Panel and switch on Air Supply
	System to the pilot Plant.
2	Fill the vessel VE-510 and VE-520 with water until it is about high-
	level
3	Ensure that DCS is ready
4	Start up the DCS client computer. Go to homepage and then perform
	the login experiment operation.
	Select Experiment 9 : Flow Ratio Control Auto Tuning (FIC-
	513/523-POS)
5	Open or close hand valves at the Pilot Plant as follows:
	- Open Hand Valve HV 500
	- Open Hand Valve HV 511
	- Open Hand Valve HV 521
	- Open Hand Valve HV 512
	- Open Hand Valve HV 523
	- Open Hand Valve HV 530
	- Open Hand Valve HV 531
	- Close others
6	Set the controller FIC-513 and FIC-523 to manual mode
7	Close the control Valve FY-513A and FY-523A manually (0% open)

Section A2

STEP	ACTION
1	Using the printed graph from section A.1 above, note down the
	ultimate gain Ku, and determine the ultimate period, Pu for FIC-513
2	Based on the Ziegler-Nichols Closed loop tuning correlation in the
	data, calculate the controller turning parameters for the following
	modes:
	- Proportional-only (P only mode)
	- Proportional-Integral (PI)
	- Proportional-Integral-Derivative (PID)
3	Ready to test the performance of each controller and the flow control
	loops.
	Each mode must be tested, using the tuning parameters for one
	controller at a time.

Section B: Control loop Performance Test

Section B1: Start experiment

Conduct the experiment according to the verified procedures. Test the controller using the set points change from 1.5 to 2 m3/h.

STEP	ACTION
1	Using data trends obtained from Section B1, determine relevant
	performance measures in order to analyze and compare the
	performance of the controllers (such as decay ratio, MV overshoot,
	settling time, rise time, etc.)
2	Evaluate the Data
3	Choose the controller with the best performance for secondary loop
	to proceed to Section C.
	- Operate the flow ratio control system with varying flow rates
	on the primary loop, FIC-513

Section C: Flow ratio control system with Open Primary Flow Loop

Continue the experiment from section B1
Ensure that the controller FIC-523 is set to at Manual Mode. Set the
best controller for secondary Controller FIC-523 chosen in Section
B2
Adjust the Set Point (SP) of FIC-523 to O m3/h. manually increase
the opening of FY-523 to 50%
Start Pump P521 via the computer
Wait the Flow curve FIC-523 to reach a steady state value.
Ensure that the primary Controller FIC-513 is set at manual mode.
Increase its MV manually to 50%
Start pump P511 via the computer
Wait the FT-513 t reasonable stabilized to a steady state value.
Set K factor to 1.0
Set the secondary controller FIC-523 to remote status bu selecting
the L/R (Local/Remote) button on its faceplate.
The set point of secondary controller FIC-513 should not reflect the
current flow rate of FT-513. See that FIC-523 is able to control its
PV to stabilize at its new set point.
Collect the data from the freeze mode of the process response,
denoting K factor and the amount of both flow rates, FT-513 and
FIC-523

Section D: Primary Flow Loop Tuning using Ultimate Sensitivity Test

STEP	ACTION
1	Continue the experiment from section C
2	Ensure that the secondary controller FIC-523 is still in remote mode and
	K factor is set at 1.0
3	Set the primary controller FIC-513 in manual mode.
4	Adjust the set point of FIC-513 to 1.5 m3/h. Then, manually set to its
	MV to 50%
5	Wait for flow curve FT-513 to reach a steady state value close to 1.5
	m3/h. observe the set point of secondary controller FIC-523 should now
	reflect the current flow rate of FT-513
6	See that FIC-523 is able to control its PV properly and wait for the PV

r	
	to stabilize at its new set point
7	At the primary controller FIC-513 faceplate, set the controller Gain (P)
	to 0.5, the Integral time (I) to 9999, and the Derivative time (D) to 0
8	Set the controller (FIC-513) to Auto mode. Wait for the process Value
	(PV) to stabilize
9	Make a small step change to the set point by increasing it to 2.0 m3/h
10	Observe the process Value (PV), FT-513 from the trend window. If the
	PV response is not oscillatory, double the controller gain (P) value until
	it becomes oscillatory.
11	If the PV response is oscillatory, observe whether the magnitude of PV
	is increasing or decreasing.
	- If increase, reduce controller gain by 1.5 times
	- If decrease, increase controller gain by 1.5 times
12	When constant amplitude oscillation is achieved, allow up to 3 or more
	oscillation cycles to be recorded and freeze the trend window.
13	Evaluate the Data from the graph.

Section E: Flow Ratio Control System with Closed Loops

STEP	ACTION
1	Continue the experiment from the section D.3. Ensure that the
	secondary controller FIC-523 is still in Remote mode and K factor is 1.0
2	Set the Primary Controller FIC-513 to manual mode. Key in the
	secondary controller tuning parameters chosen in section D.4
3	At the controller Faceplate FIC-513, and adjust its Set Point (SP) to 1.5
	m3/h
4	Manually increase MV of FIC-513 to 50%. Wait for the PV to stabilize
	at a steady state value
5	Set the primary controller FIC-513 to Auto mode
6	Introduce a small set point change at primary controller FIC-513 to 2.0
	m3/h
7	See the FIC-523 is able to control its PV properly.
8	Observe that the set point at FIC-523 will change according to the flow
	rate change at FT-513
STEP	ACTION
9	Evaluate the process response
10	Change the K factor to 0.5
11	Record the change in set point and process value (PV) of FIC-513. Wait
	until both curves (FT-513 and FIC 523) are able to stabilize at their
	respective set points.
12	Capture the important process responses and print out the trend curves
	data.