A Control Evaluation on a Slurry-Filled Sump

By

Amir Azuan bin Shamsudin

Dissertation submitted in partial fulfillment of
the requirements for the
Bachelor of Engineering (Hons)
(Chemical Engineering)

JANUARY 2005

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CERTIFICATION OF APPROVAL

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A project dissertation submitted to the
Chemical Engineering Programme
Universiti Teknologi Petronas
in partial fulfillment of the requirement for the
BACHELOR OF ENGINEERING (Hons)
(CHEMICAL ENGINEERING)

Approved by,

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CERTIFICATION OF ORIGINALITY

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

(AMIR AZUAN BIN SHAMSUDIN)

ABSTRACT

Sump can be defined as a reservoir which is normally located at the downstream of a process, from which water is pumped where solids accumulates. Sump is a system which faces instability due to its dynamic behaviors. Application of control strategies to the sump might add some advantages in handling the sump, where in some process, sump plays a significant role especially when it involves in a process that have highly hazardous stage. This project studies generally observe the behavior of the sump by adapting control type such as the feedback, Smith predictor, feedforward, and cascade control. In addition, the sump is adapted with a neurocontrol from Neural Network Control strategies. The neurocontrol used is the NARMA-L2 controller. The variation of simulation have resulted in a way that majority of the controller are at highest performance when the percentage of solids in is 80%. The application of neurocontrol to the system somehow does not meet the target due to high error that the controller sustained. However, the neurocontrol can be enhanced more by data training and this is recommended for further research by using other neurocontrol that is available in the Neural Network control strategies.

ACKNOWLEDGEMENT

A Control Strategies Study of a Slurry-Filled Sump took approximately four months to be completed, compile and edited. The period of four months of the project studies was the most useful and beneficial moments of knowledge in my life as a final year student completing the Bachelor of Engineering (Hons.) Chemical Engineering courses in University Teknologi PETRONAS.

My highest gratitude to The Almighty Allah S.W.T, for giving me the great health, sufficient energy and fruitful ideas which have enabled me to complete this project studies. Without His Willingness, there might not be any studies that can be implemented by me. For that, I am humbly thankful for all the gifts that Allah has given me. Alhamdulillah.

To my beloved parents, Mr. Shamsudin Abdul Majid and Pn. Zaharah Buyong, there is nothing in this world that can replace every single thing that you both have been doing for me all this while. Your tender love, sincere care and concern towards me are too much that I myself can never payback for the rest of my life.

Million thanks to my dedicated and kind-hearted supervisor, Mr. Mohd Nasser Ramli, who have been sacrificing his time guiding me from day one until the end of my project studies. His contributions, guidance, and feedbacks towards my project studies have helped me a lot especially during my rough time.

I would also like to express my appreciation to Pn. Yuliana Yuhana, the coordinator of the FYRP course of July 2004 semester, and also the FYRP committee in general. Their effort is highly appreciated in ensuring that this course will give maximum benefits to both lecturers and students.

Last but certainly not least, to all my friends and colleagues, who have been given me a spark of spirit to endure every single obstacle in completing this project studies. A bunch of thanks I dedicated to each and every one of you who play significant role in my life.

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CHAPTER 1
INTRODUCTION

1.1 Background of Study

Sump can be defined as a reservoir which is normally located at the downstream of a process, from which water is pumped where solids accumulates. Alternatively, sump also functioned as a recycle reservoir. It handles a combination of two main components, which are water and solid. Sump is widely used in the industry such as mining and minerals industry and even in hydrocarbons processing industry. Taking an example from a nuclear plant where it signifies the importance of a sump in processing industry. In the nuclear plant, sump is a part of the Emergency Core Cooling System which is required in every nuclear plant. The sump play significant role in the cooling system collects reactor coolant and chemically reactive spray solutions following a loss-of-coolant accident. The sump serves as the water source to support long-term recirculation for the functions of residual heat removal, emergency core cooling, and containment atmosphere cleanup. This water source, the related pump inlets, and the piping between the source and inlets are important safety components. In the hydrocarbon processing industry, a wet sump lubrication are used to prevent the intrusion of airborne contaminates commonly used on sleeve or plain bearings and in gearboxes.

In the industry, many processes have an unstable integrator dynamics. Sump is one of the processes that are unstable. The unstability relies on its level variation. Therefore it is essential to ensure that the level of the sump is under a good and effective control in order to avoid any occurrence of overflow of the sump tank. The adaptation of control strategies is important nowadays since the sump is one of the important components in the safety criteria of certain processes.

1.2 Problem Statement

The main criteria that in stressed along the studies is the adaptation of the Advanced Control Type to the sump system. This is in order for the system involving the sump to have a better control of its crucial criteria, which is the level. Problems arise only when the main control method used which is mainly the proportional-only control is too simple and does not fully comply with nowadays requirement.

The behavior of the sump need to be determined since different process will require different behavior of the sump. For example, reported by Gopinath, the percentage sump level varies under the controller is off and maintained steady at constant percentage level with the controller is on. Even certain assumption must be made in order to simplify the studies of the sump behaviors.

Prior to the completion of the study, several control strategies alternatives are made available and tested its reliability and performance in the processing industry. The recommended control strategies can be a reference in future for further enhancement of the system involving the sump.

1.3 Objectives and Scope of Study

The objectives of the studies are:

1. to study the behavior of a sump
2. to determine the problem of the existing control strategies of a sump
3. to identify possible type of advanced control strategies that could be implemented on to a sump
4. to come out with a proper advanced control strategies of a sump

The scope of the studies is to enhance the control system of the sump. The main criteria monitored when controlling the sump is the level. This can be done by applying the advanced control strategies. In this study, the Advanced Control Strategies adapted are as follow:

- Feedback Control System
- Smith Predictor Control Method
- Feedforward Control System
- Cascade Control
- Neural Network System

The study will lead to the development of possible and feasible advanced control strategies that could be implemented to the processes involving sump.

CHAPTER 2

THEORY AND LITERATURE REVIEW

2.1 Dynamic Modeling of a Sump

The assumption leading to the model is that the agitator suspends the slurry in the sump, uniform mixing in the sump and no particle size change are assumed to occur. The dynamic behavior of the sump is as follows:

$$\frac{dm_{solid}}{dt} = m_{solid\ in} - m_{solid\ out} \tag{1}$$

$$\frac{dm_{water}}{dt} = m_{water\ in} - m_{swater\ out} \tag{2}$$

$$\frac{m_{solids}}{m_{water}} = \frac{m_{solid,out}}{m_{water,out}} \tag{3}$$

$m_{solid,in}$ is solid mass flow rate in, $m_{solid,out}$ is solid mass flow rate out, $m_{water,in}$ *is* water mass flow rate in and $m_{water,out}$ is water mass flow rate out.

$$slurry\ volume\ in\ sump = \frac{m_{solids}}{\rho_{solid}} + \frac{m_{water}}{\rho_{water}} \tag{4}$$

$$level = \frac{slurry\ vol}{sump\ vol}$$

The dynamic modeling for the sump studied is for two components in the sump, which is the solid and the water. The dynamic modeling mass balance is an ordinary differential equation (ODE). The various methods to solve the equation are by using integration, numerical integration, algebraic solution and simulation in Matlab.

The first task in the model was to determine the mass of solid and the mass of water in the sump, slurry volume and level in the sump. The equation was solved using simultaneous equation. The initial condition at time t = 0, the mass of solid and the mass of water is 40 tonnes and 30 tonnes respectively. The specific gravity for the solid is 2.65 and the water was taken as 1.0. The sump volume is 50 m^3.

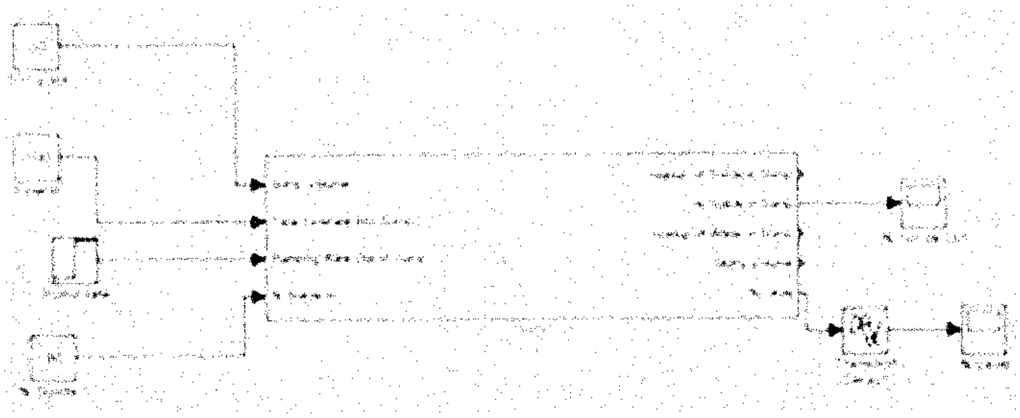

Figure 1: *The diagram for modeling of the sump in manual mode in MATLAB*

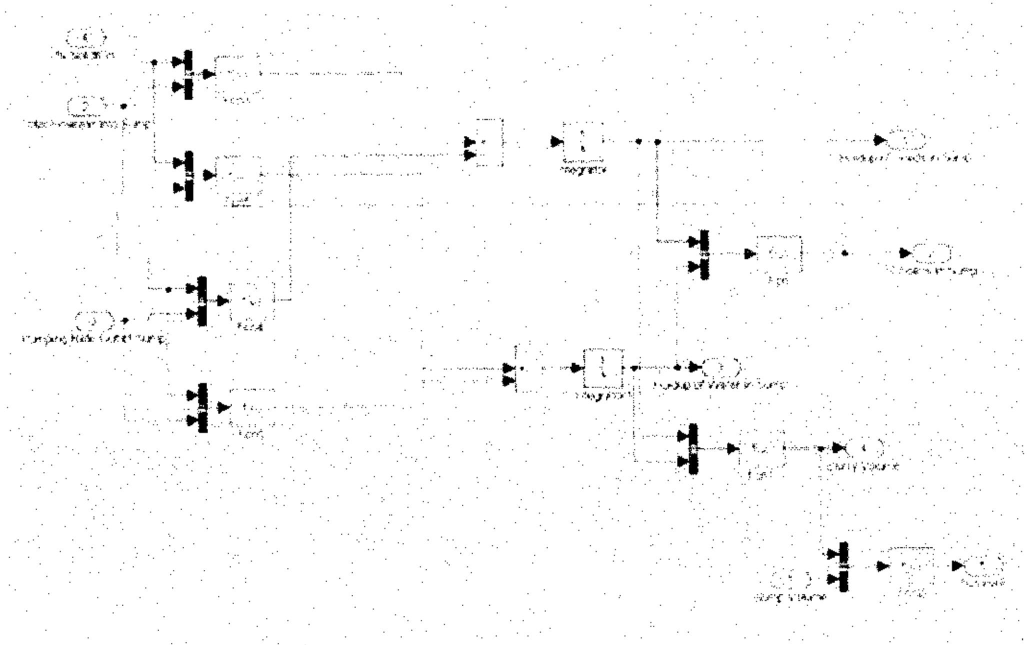

Figure 2: *The diagram for subsystem of the sump in MATLAB*

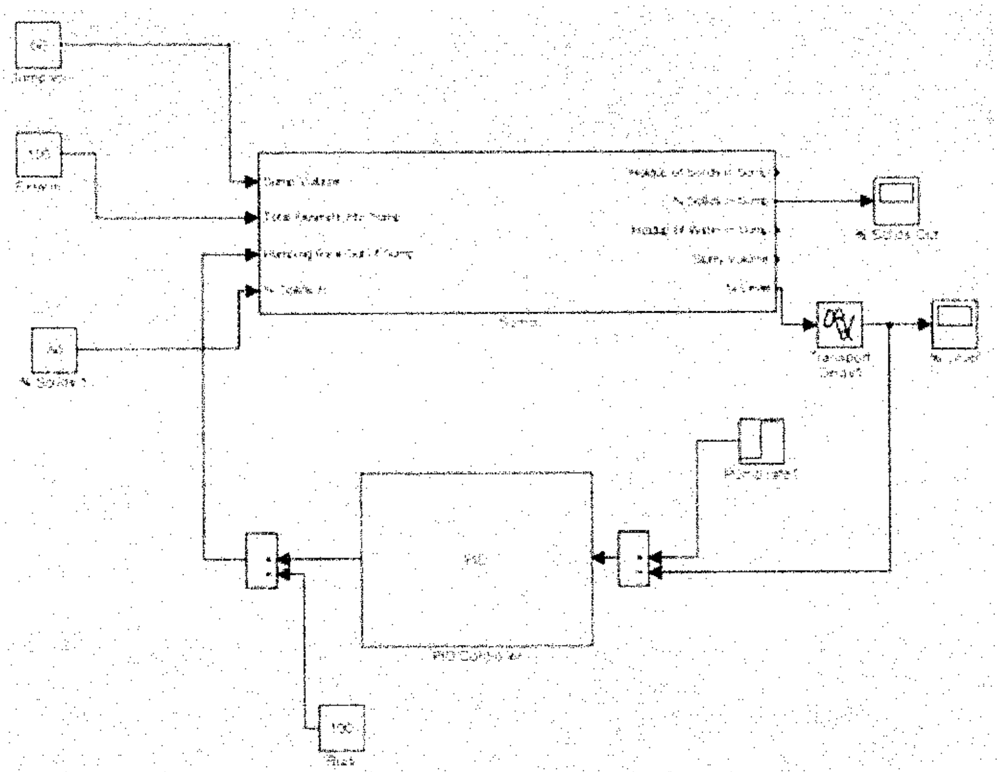

Figure 3: *The diagram for modeling of the sump in automatic mode in MATLAB*

2.2 Sump Controller Tuning Value

From the tuning done by M.N Ramli, the proportional and integral time value for the PI controller is determined. The tuning was done for the open loop tuning for unstable processes. The studies were done by manipulating the pumping rate of the sump tank. When the step change was made at the pumping rate of 1, the process variable (PV) falls at a continuous rate and the PV trend behaves like a ramp. The shape has two important criteria which is:

1. The slope of the process output is ramp
2. The time passes before the output starts to change

The process could be described using two parameters:

1. The unstable process gain ($K_{unstable}$)
2. The dead time (T_D)

The unstable process gain is calculated as follows:

$$K_{unstable} = \frac{Slope\ of\ PV}{\Delta MV} = \frac{\left[\frac{\Delta PV}{\Delta Time}\right]}{\Delta MV}$$

The dead time is calculated as before but the response shows a small dead time. The unstable gains ($K_{unstable}$) are illustrated on the following diagram:

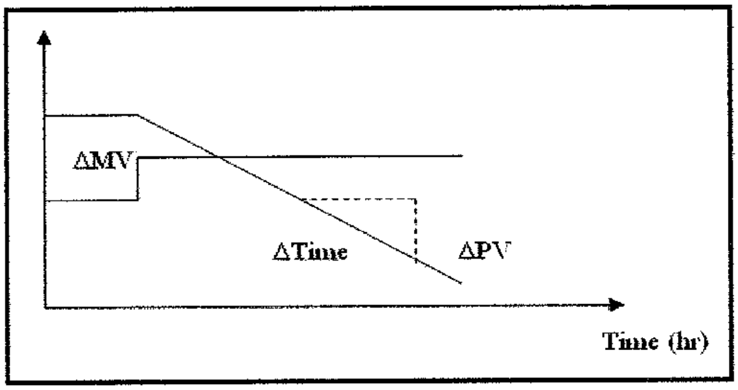

Figure 4: *Relation between PV and MV with Time*

The results from the tuning process done in this stage are listed as below, where three percentage of amount of solids inside the sump tank were taken in to consideration. The values obtained due to the tuning done are as follow:

For 40 % of Solid in,

Tuning	Proportional	Integral
1	1.0077	0.1111
2	1.0050	0.1250
3	1.0075	0.1333
4	0.9950	0.1667
5	1.0002	0.1429

Table 1: ***P-I Value for 40 % Solid In***

For 60 % of Solid in,

Tuning	Proportional	Integral
1	1.000	0.1667
2	0.9949	0.1852
3	0.8062	0.1724
4	0.8021	0.1887

Table 2: ***P-I Value for 60 % Solid In***

For 80 % of Solid in,

Tuning	Proportional	Integral
1	1	0.2381
2	1.2533	0.3571
3	1.2520	0.3846

Table 3: ***P-I Value for 80 % Solid In***

2.3 Controller Type

2.3.1 Feedback Controller

Feedback control starts as early as 250 B.C. The feedback controller was used by the Greeks to control the level of water of their water system. The mode of operation is similar to the level regulator in the modern life flush toilet. James Watt applied the fly-ball governor to his new engine steam in 1788, where it played a significant role in the development of the steam power. Here, feedback control was essential for the development of high-gain, operational amplifier that are widely used in electronic equipment in the 1930s.

In the 1930s, the three-mode controller with proportional, integral, and derivative (PID) feedback control action was commercially available. During this period also, the first theoretical papers on process control were published. This is the starting point of the enhancement of the usage of the controller application in the industries.

The three basic feedback control modes that are employed are proportional (P), integral (I), and derivative (D) control. Consider the flow control system show below, where the process stream is measured and transmitted electronically to the flow controller. The controller will eventually compare the measured value to the set point value and hence, taking the appropriate corrective action by sending the output signals to the control valve.

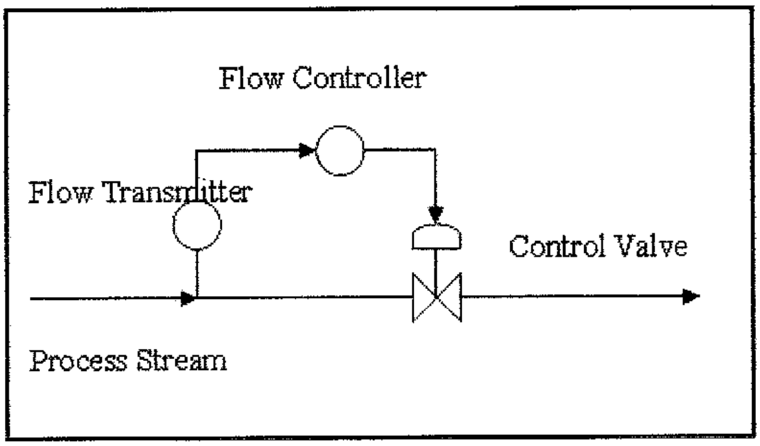

Figure 5: *Example of Feedback Controller*

2.3.2 Smith Predictor Controller

Theoretically the Smith Predictor Control Method is a special control strategy that is best to be used in order to improve the performance of time delay systems. Time delays commonly occur in the process industries because of the presence of distance velocity lags, recycle loops and the dead time associated with composition analysis. The presence of time delays in the process limits the performance of a conventional feedback control system. From a frequency response perspective, time delay add phase lag to the feedback loop, which adversely affects closed-loop stability.

The Smith predictor is referred to as model-based controller, as is Internal Model Control (IMC). This is because the control strategy utilizes the model parameters directly. Various investigators found that the performance of Smith predictor for set-point change can be as much as 30% better than a conventional controller based on an integral squared error criterion.

The model-based controller like Smith predictor approach required a dynamic model of the process. If the process dynamics change significantly, the predictive model will be inaccurate and the controller performance will deteriorate to a point of instability. For such processes, the controller should be tuned conservatively to accommodate possible model errors. Schlek and Hanesian once performed a detailed study analyzing the effect of model errors on Smith predictor for a first order plus time-delay model. They found that if the assumed time delay is not within 30% of actual process time delay, the predictor is inferior to a PI controller with no time-delay compensation. If the time-delay varies significantly, it may be necessary to use some sort of adaptive controller to achieve satisfactory performance.

Previously, the Smith predictor is seldom implemented as a continuous (analog) controller due to the difficulty of approximating time delays with analog components. However with the introduction of the digital version of Smith predictor, this problem can be avoided.

2.3.3 Feedforward Controller

The main concept of the Feedforward control is to take corrective action before they upset the process. The difference between feedback controls here is where the feedback control does not take corrective action until after the disturbance upset the process. Feedforward control will suppress the disturbance before it has had the chance to affect the system's essential variables. This requires the capacity to anticipate the effect of perturbations on the system's goal. Otherwise the system would not know which external fluctuations to consider as perturbations, or how to effectively compensate their influence before it affects the system. This requires that the control system be able to gather early information about these fluctuations. For example, feedforward control might be applied to the thermostatically controlled room by installing a temperature sensor outside of the room, which would warn the thermostat about a drop in the outside temperature, so that it could start heating before this would affect the inside temperature.

In many cases, such advance warning is difficult to implement, or simply unreliable. For example, the thermostat might start heating the room, anticipating the effect of outside cooling, without being aware that at the same time someone in the room switched on the oven, producing more than enough heat to offset the drop in outside temperature. No sensor or anticipation can ever provide complete information about the future effects of an infinite variety of possible perturbations, and therefore feedforward control is bound to make mistakes. With a good control system, the resulting errors may be few, but the problem is that they will accumulate in the long run, eventually destroying the system.

In majority practical application, feedforward controls normally were used together with the feedback control. The pairing of these controllers will have the feedforward control to reduce the effect of measurable disturbances while the feedback control will tend to trim compensation for inaccuracies in the process model, measurement errors and unmeasured disturbances.

2.3.4 Cascade Controller

Cascade control is a control strategy in which one control loop provides the set point for another loop. It allows the process to reach quickly its set point while minimizing overshoot. The two loops are commonly known as the master (primary) loop and the slave (secondary) loop. The output signal of the master loop that will serves as the set point for the slave loop. The cascade controller consists of two feedback control loops where the two loops are nested with the slave loop located inside the master loop. The slave controller controls another faster variable that affects the first variable. The master controller positions the set point of the secondary controller and it, in turn manipulates the control valve. The primary variable is slow, most commonly the temperature, while the secondary variable is much as ten time faster, usually flow. The secondary loop is introduced to reduce lags, thus stabilizing inflow to make the whole operation more accurate and responsive. The secondary controller may be regarded as an elaborate final control element, positioned by the primary controller in the same way a single controller would ordinarily position the control valve. For example, the secondary controller is a flow controller, then the primary controller will not be dictating the prescribe flow (set point).

Cascade control can improve control system performance over single-loop control whenever either:

- Disturbances affect a measurable intermediate or secondary process output that directly affects the primary process output that we wish to control; or
- The gain of the secondary process, including the actuator, is nonlinear.

In the first case, a cascade control system can limit the effect of the disturbances entering the secondary variable on the primary output. In the second case, a cascade control system can limit the effect of actuator or secondary process gain variations on the control system performance. Such gain variations usually arise from changes in operating point due to set point changes or sustained disturbances.

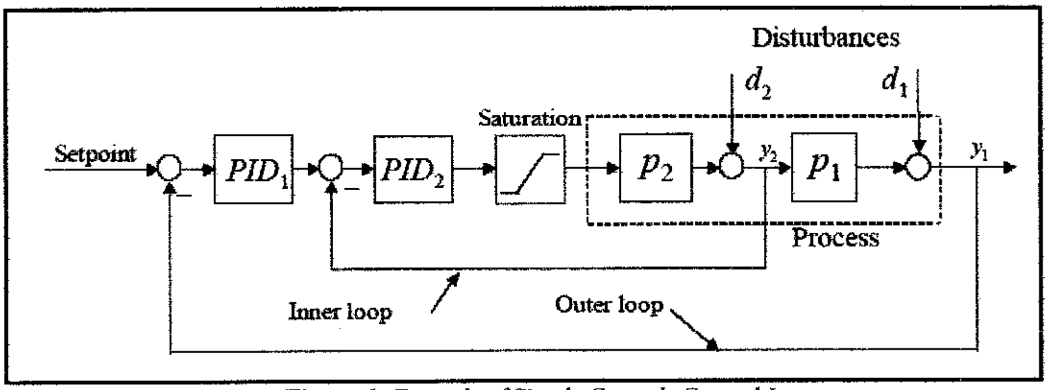

Figure 6: *Example of Simple Cascade Control Loop*

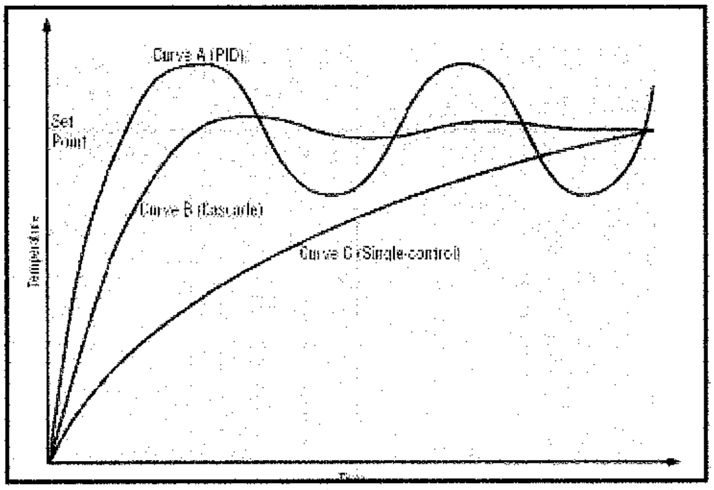

Figure 7: *Example Showing the Control Performance of Cascade Control Over Single Control and Simple PID Control*

2.3.5 Neural Network Controller (NARMA-L2)

The history of neural networks begins with the earliest model of the biological neuron given by McCulloch and Pitts in 1943. This model describes a neuron as a linear threshold computing unit with multiple inputs and a single output of either 0, if the nerve cell remains inactive, or 1, if the cell fires. A neuron fires if the sum of the inputs exceeds a specified threshold. In functional form, this gives $f(x) = 1$ for x greater than some threshold, and $f(x) = 0$ otherwise (this is commonly known as the indicator function) [50]. In theory, such a "system" of neurons presents a possible model for biological neural networks such as the human nervous system. The McCulloch and Pitts model was utilized in the development of the first artificial neural network by Rosenblatt in 1959. This network was based on a unit called the perceptron, which produces an output scaled as 1 or -1 depending upon the weighted, linear combination of inputs. Variations on the perceptron-based artificial neural network were further explored during the 1960s by Rosenblatt and by Widrow and Hoff, among others.

According to Howard Demuth and Mark Beale in Neural Network Toolbox For Use in MATLAB, Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. Neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this *supervised learning*, to train a network.

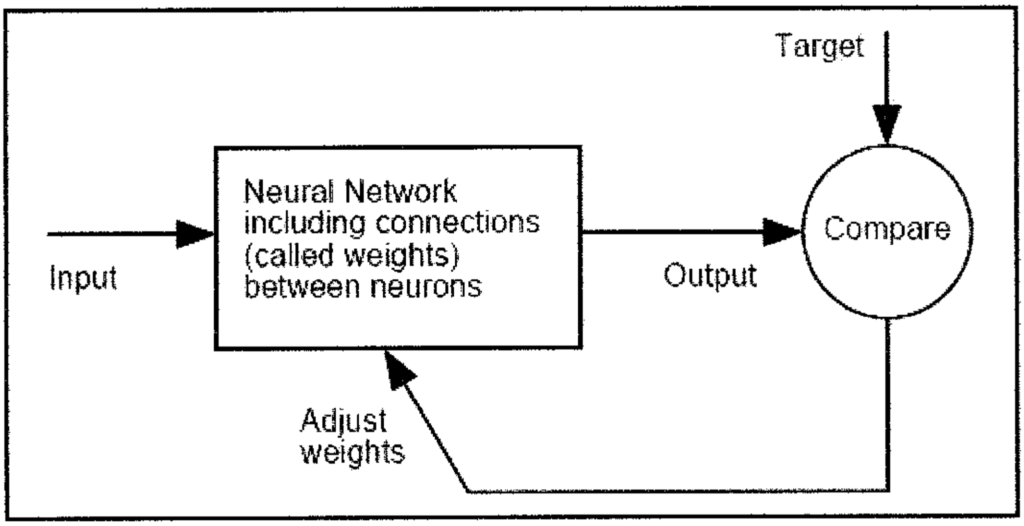

Figure 8: *How Neural Network Functions*

Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as "on line" or "adaptive" training. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings. Throughout the toolbox emphasis is placed on neural network paradigms that build up to or are themselves used in engineering, financial and other practical applications

The supervised training methods are commonly used, but other networks can be obtained from unsupervised training techniques or from direct design methods. Unsupervised networks can be used, for instance, to identify groups of data. Certain kinds of linear networks and Hopfield networks are designed directly. In summary, there are a variety of kinds of design and learning techniques that enrich the choices that a user can make.

CHAPTER 3

METHODOLOGY/PROJECT WORK

3.1 Simulation Procedure in MATLAB Programme

First stage of the study is to determine the dynamic equation for the sump. The equation is then modeled in the MATLAB Simulink as a subsystem. The subsystem is next put under masked. The input for the masked subsystem is the total flow rate into the sump. The percentage solids in, volume, and pumping rate out of the sump, is modeled as constant value inside the masked subsystem.

The out flow for the masked subsystem is the percentage of solids in the sump, the percentage of level in the sump, the holdup for solid and water and the slurry volume inside the sump. The main parameter that is monitored along the study is the percentage level of the sump because as mentioned before, the main objective is to avoid any overflow condition to the sump.

Then next step is the simulation of the sump system. The simulation was done by implementing the control method to the sump system. The methods are as follow:

- Feedback Control
- Feedforward Control
- Cascade Control
- Smith Predictor
- Neural Network Control

Generally, for all set of controller listed above, the work procedure is basically identical to each other. The total flow rate of the sump was set at 100 tonnes/hr. The volume of the sump was fixed at 50 m^3 and the percentage solid in was 40%. The step size for the manipulated variable was at 5 total flows and the step time was at 5 hour. The output of the process, PV was obtained. The step size is then increased to 7.5 and the step time was maintained. Again, the process output, PV obtained and the difference is compared. After that the step size is further increased to 10 with the same step time as previous sample.

The procedure in manual mode was repeated for the percentage input of the solids in was at 60% and 80% respectively. The value of the proportional gain and the integral was input into the PID controller and the controller was put in automatic mode. After that a step change in the total flow 1 set point at step time of 5 hr and the step size at 15 total flows. The procedure was repeated for the percentage of solids in at 60% and 80% respectively. Each of the system is stipulated with load changes to observe the controller action due to the changes. Therefore the performance of the controller can be monitored.

3.2 Controller Tuning

The tuning for each controller done based on the literature tuning value obtained. The tuning that was selected for the sump dynamic model, were the IMC method open loop tuning for the unstable process. The process has unstable integrator dynamics for the sump level. The IMC method calculates the tuning based on the characteristics plus the controller time constants (T_C):

Proportional Gain:

$$K_p = \frac{1}{K\left(\tau_C + \frac{T_D}{2}\right)}$$

Integral Gain: A value determined to eliminate offset after disturbances

Derivative Gain: 0

The integral gain in set to a small value, as integral will tend to further destabilize these processes

3.3 Neural Network Procedure

The simulation procedure for Neural Network in MATLAB is somewhat quite different from other conventional controller. Firstly, the type of network controller is chosen. In this case study, the NARMA-L2 Controller is chosen and several simulations to the sump system were done in order to observe the behavior of the network toward the sump system.

The plant identification of NARMA-L2 controller will require the user to determine some parameters. Those parameters can be viewed from the figure below.

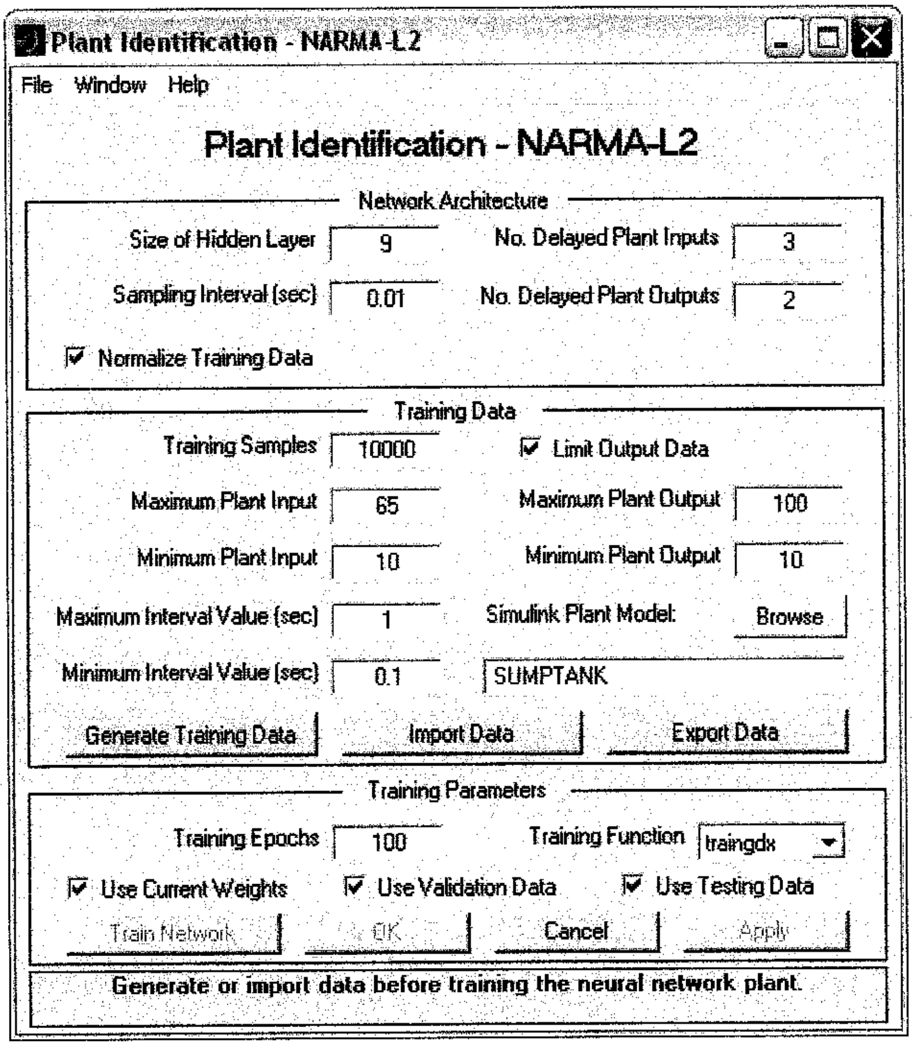

Figure 9: *Plant Identification of NARMA-L2 Controller*

The next step is to generate the data that have been specified. The sump dynamic modeling which has been modeled in the SIMULINK is included in the Plant Identification as the SIMULINK Plant model. Once the data generation is done, the system is taken to the next step of training the data. Two training functions were used during the simulation of the sump system. The training functions used were the *trainlm* and *traingdx*. The training of the system is proceeded until the performance of the neural network approaching its goal, which is 0. The values in the Network Architecture of the Plant Identification are manipulated in order to get the performance gradient closer to 0. Then the simulation in the simulation workspace is done to observe the response of the controller towards the sump system.

3.4 Tool for Study

Since the study is about the simulation of the sump process control, the simulation tool used in the study is the MATLAB Programme which applies the SIMULINK application.

CHAPTER 4
SIMULATION RESULTS AND DISCUSSION

4.1 Simulation Results

Tuning values obtained from literature review were used as the basis for tuning the controller type that will be discussed in this paper, which are the Feedback Controller, Smith Predictor Method Controller, Feedforward Control and Cascade Control. The result obtained is compared to each other with the value of the solids in varied (40 %, 60 %, and 80 %).

4.1.1 Feedback Controller

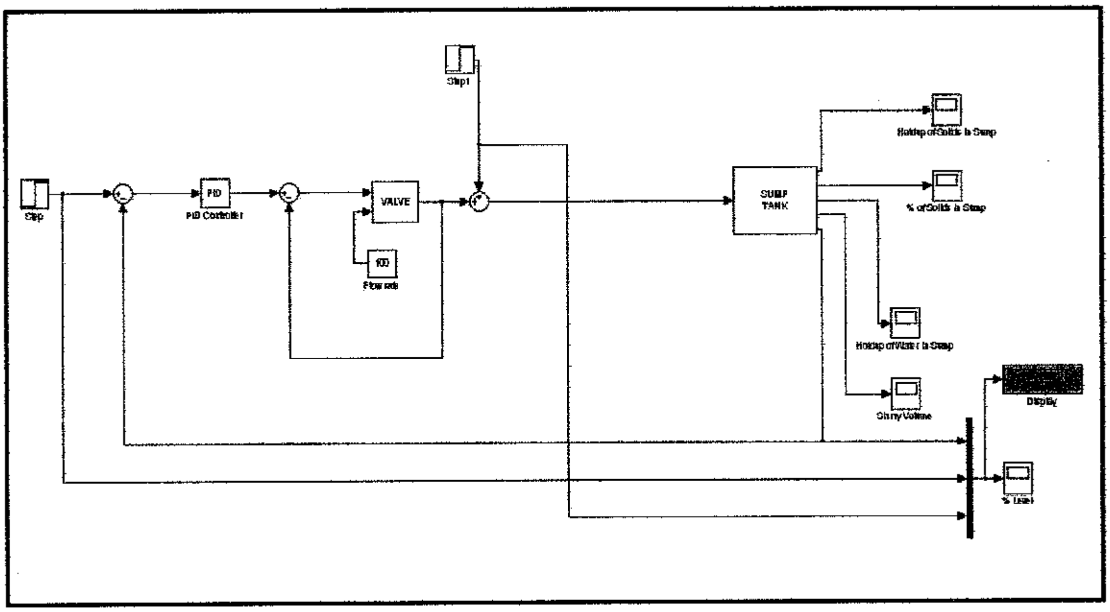

Figure 10: ***Feedback Controller Diagram of a Sump Tank***

The sump control loop in the diagram utilizes the application of the Feedback Control Strategies. The process was put under simulation for three different values of Flow of solids in to the sump. The initial value is 40 %. The value is then further increased to 60 % and finally 80 % of solids flow in. The results of the simulation can be viewed in the Appendices. From the results available, the best tuning for each set of data (40 %, 60 %, and 80 %) is determined and compared to each other.

For 40 % of flow of solids in, the best tuned graph obtained was the graph of Tuning 4, where the value of the PI controller is P = 0.9950, and I = 0.1667. The summary results for Tuning 4 are as follows:

Solid	40	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	1.338
Flow of Solid in	40	**Sump Water Hold Up**	1.989
Flow of Water in	60	**Solid Density**	2.65
Vol. Flowrate Solid	15.0943	**Water Density**	1
Vol. Flowrate Water	60	**Load Time**	10
Residence Time	0.66582	**Load Size**	10

Table4: *Result Data of Simulation for 40 % Solid in Flow (Feedback)*

For 60 % of flow of solids in, graph of Tuning 4 is the best. The data of the result are as follows:

Solid	60	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	2.394
Flow of Solid in	60	**Sump Water Hold Up**	1.597
Flow of Water in	40	**Solid Density**	2.65
Vol. Flowrate Solid	22.6415	**Water Density**	1
Vol. Flowrate Water	40	**Load Time**	10
Residence Time	0.79819	**Load Size**	10

Table5: Result Data of Simulation for 60 % Solid in Flow (Feedback)

For 80 % of flow of solids in to the sump, the graph of Tuning 3 gives the best simulation results compared to the other tuning values. The data results are as follows:

Solid	80	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	3.984
Flow of Solid in	80	**Sump Water Hold Up**	0.997
Flow of Water in	20	**Solid Density**	2.65
Vol. Flowrate Solid	30.1887	**Water Density**	1
Vol. FlowrateWater	20	**Load Time**	10
Residence Time	0.9962	**Load Size**	10

Table6: *Result Data of Simulation for 80 % Solid in Flow (Feedback)*

4.1.2 Smith Predictor Controller

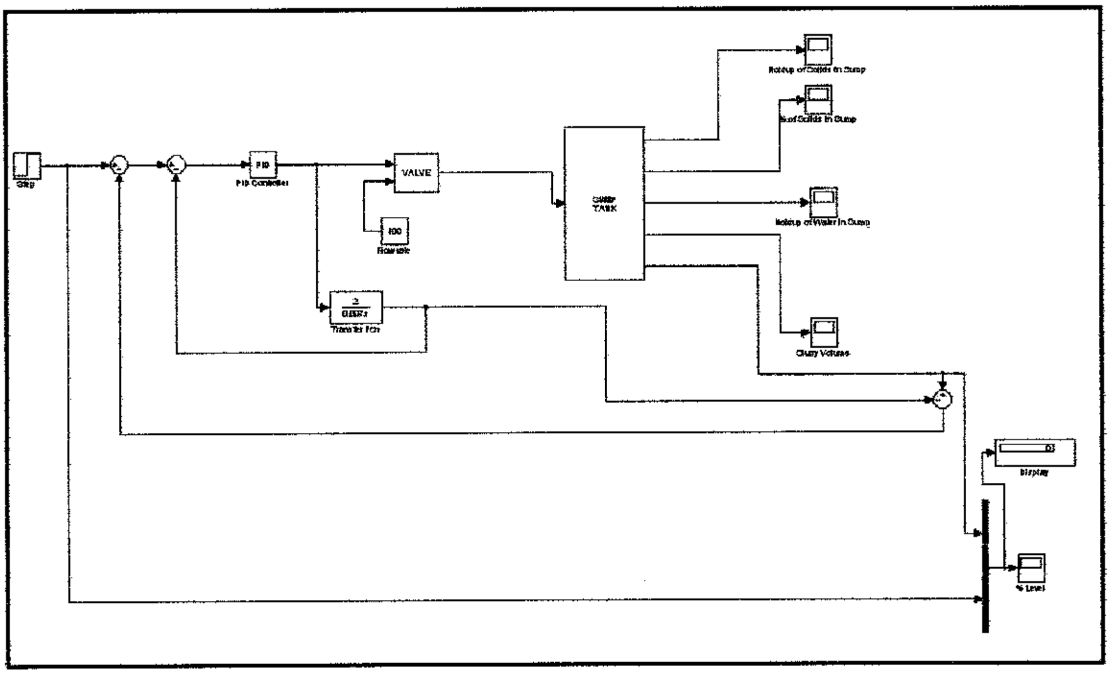

Figure 11*: **Smith Predictor Controller Diagram of a Sump Tank***

Figure 11 above illustrate the sump system where the Smith Predictor Controller Method is applied. The manipulated variable is still the solids flow in to the sump. The step size is

5 % of solid flow in with step time of 5 hours. The value for the PI controller was also obtained from the literature. The initial value is 40 %. The value is then further increased to 60 % and finally 80 % of solids flow in.

For 40 % of flow of solids in, the best performing graph is the graph of Tuning 5.

Solid	40	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	1.333
Flow of Solid in	40	**Sump Water Hold Up**	1.996
Flow of Water in	60	**Solid Density**	2.65
Vol. Flowrate Solid	15.0943	**Water Density**	1
Vol. Flowrate Water	60	**Load Time**	10
Residence Time	0.66582	**Load Size**	10

Table7: Result Data of Simulation for 40 % Solid in Flow (Smith Predictor)

For 60 % of flow of solids in to the sump tank, the best tuning is the graph of Tuning 4.

Solid	60	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	2.392
Flow of Solid in	60	**Sump Water Hold Up**	1.601
Flow of Water in	40	**Solid Density**	2.65
Vol. Flowrate Solid	22.6415	**Water Density**	1
Vol. Flowrate Water	40	**Load Time**	10
Residence Time	0.7982	**Load Size**	10

Table8: Result Data of Simulation for 60 % Solid in Flow (Smith Predictor)

For 80 % of flow of solids in to the sump, the best tuning obtained was from the graph of Tuning 3.

Solid	80	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	3.985
Flow of Solid in	80	**Sump Water Hold Up**	0.997
Flow of Water in	20	**Solid Density**	2.65
Vol. Flowrate Solid	30.1886	**Water Density**	1
Vol. Flowrate Water	20	**Load Time**	10
Residence Time	0.9962	**Load Size**	10

Table9: Result Data of Simulation for 80 % Solid in Flow (Smith Predictor)

4.1.3 Feedforward Controller

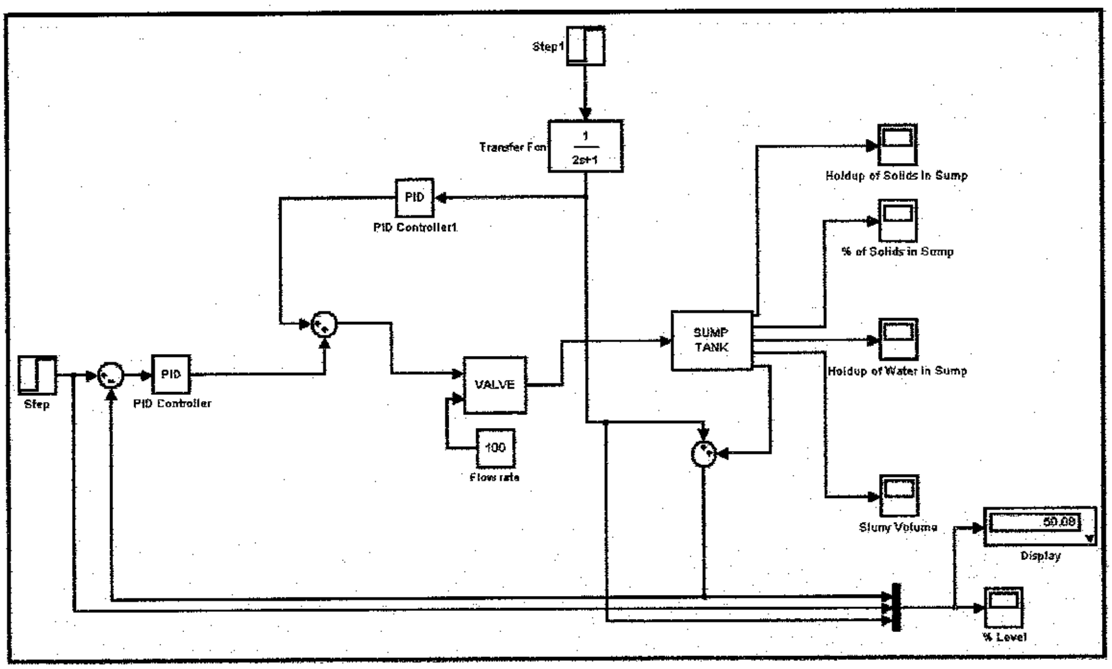

Figure 12: *Feedforward Controller Block Diagram of a Sump Tank*

Figure 12 above is the sample block diagram of a sump system using the feedforward control type. In the simulation of the sump process using Feedforward controller system, same procedure and step applies like the previous controls of feedback and the Smith predictor. The percentage of solids in is varied from 40%, increased next to 60% and finally to the value of 80% solids in. Tuning values obtained from literature was again applied to this control strategy.

When the systems is under operation value of 40% of solids in, the tuning value which is the most suitable is when the setting is at **P = 0.9950, I = 0.1667**, and **D = 0**. The result data of the simulation is shown below.

Solid	40	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	8.022
Flow of Solid in	40	**Sump Water Hold Up**	12.03
Flow of Water in	60	**Solid Density**	2.65
Vol. Flowrate Solid	15.0943	**Water Density**	1
Vol. Flowrate Water	60	**Load Time**	10
Residence Time	0.66582	**Load Size**	10

Table 10: Result Data of Simulation for 40 % Solid in Flow (Feedforward Control)

For 60% of solids in to the sump system, the controller performed the best at the PID values of **P = 1.000, I = 0.1667**, and **D = 0**.

Solid	60	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	8.022
Flow of Solid in	60	**Sump Water Hold Up**	12.03
Flow of Water in	40	**Solid Density**	2.65
Vol. Flowrate Solid	22.6415	**Water Density**	1
Vol. Flowrate Water	40	**Load Time**	10
Residence Time	0.7982	**Load Size**	10

Table 11: Result Data of Simulation for 60 % Solid in Flow (Feedforward Control)

Finally, for this control strategy, when the value of solids in to the sump is 80%, the best performing value for the controller is when **P = 1.2520, I = 0.3571**, and **D = 0.**

Solid	80	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	8.005
Flow of Solid in	80	**Sump Water Hold Up**	12.01
Flow of Water in	20	**Solid Density**	2.65
Vol. Flowrate Solid	30.1887	**Water Density**	1
Vol. Flowrate Water	20	**Load Time**	10
Residence Time	0.9962	**Load Size**	10

Table 12: Result Data of Simulation for 80 % Solid in Flow (Feedforward Control)

4.1.4 Cascade Controller

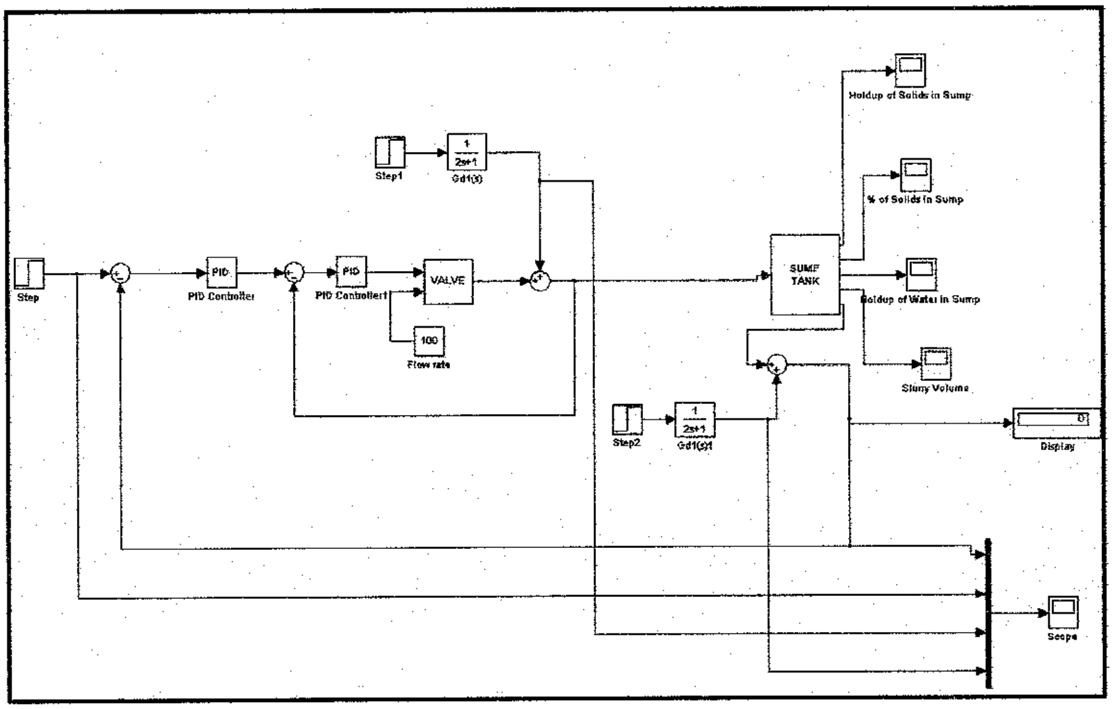

Figure 13: *Cascaded Controller Block Diagram of a Sump Tank*

Figure 11 above illustrates the block diagram of the sump system with the application of cascade control strategy. The system was again simulated with different value of percentage of solids in to the sump (40%, 60%, and 80%). The tuning values from the literature were used for the simulation matter.

For 40% of solids in, the tuning value of P = 1.0077, I = 0.1111 and D = 0 performed the best. The settling time is faster and the overshoot the system undergoes after disturbance introduced is the smallest. Result data are as listed in table below.

Solid	40	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	9.32
Flow of Solid in	40	**Sump Water Hold Up**	13.03
Flow of Water in	60	**Solid Density**	2.65
Vol. Flowrate Solid	15.0943	**Water Density**	1
Vol. Flowrate Water	60	**Load Time**	10
Residence Time	0.66582	**Load Size**	10

Table 13: Result Data of Simulation for 40 % Solid in Flow (Cascade Control)

The following tables (Table 14(60%) and Table 15(80%)) show the result data for both 60% and 80% of solids in to the system. The best controller tuning value for both set of simulations are P = 0.8062 , I = 0.1724, and D = 0, for 60% of solids and; P = 1.2520, I = 0.3846 and D = 0, for 80% of solids in.

Solid	60	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	9.55
Flow of Solid in	60	**Sump Water Hold Up**	13.98
Flow of Water in	40	**Solid Density**	2.65
Vol. Flowrate Solid	22.6415	**Water Density**	1
Vol. Flowrate Water	40	**Load Time**	10
Residence Time	0.7982	**Load Size**	10

Table 14: Result Data of Simulation for 60 % Solid in Flow (Cascade Control)

Solid	80	**Step Time**	5
Flow In	100	**Step Size**	5
Sump Volume	50	**Sump Solid Hold Up**	9.26
Flow of Solid in	80	**Sump Water Hold Up**	14.01
Flow of Water in	20	**Solid Density**	2.65
Vol. Flowrate Solid	30.1887	**Water Density**	1
Vol. Flowrate Water	20	**Load Time**	10
Residence Time	0.9962	**Load Size**	10

Table 15: Result Data of Simulation for 80 % Solid in Flow (Cascade Control)

4.1.5 Neural Network (NARMA-L2 Controller Type)

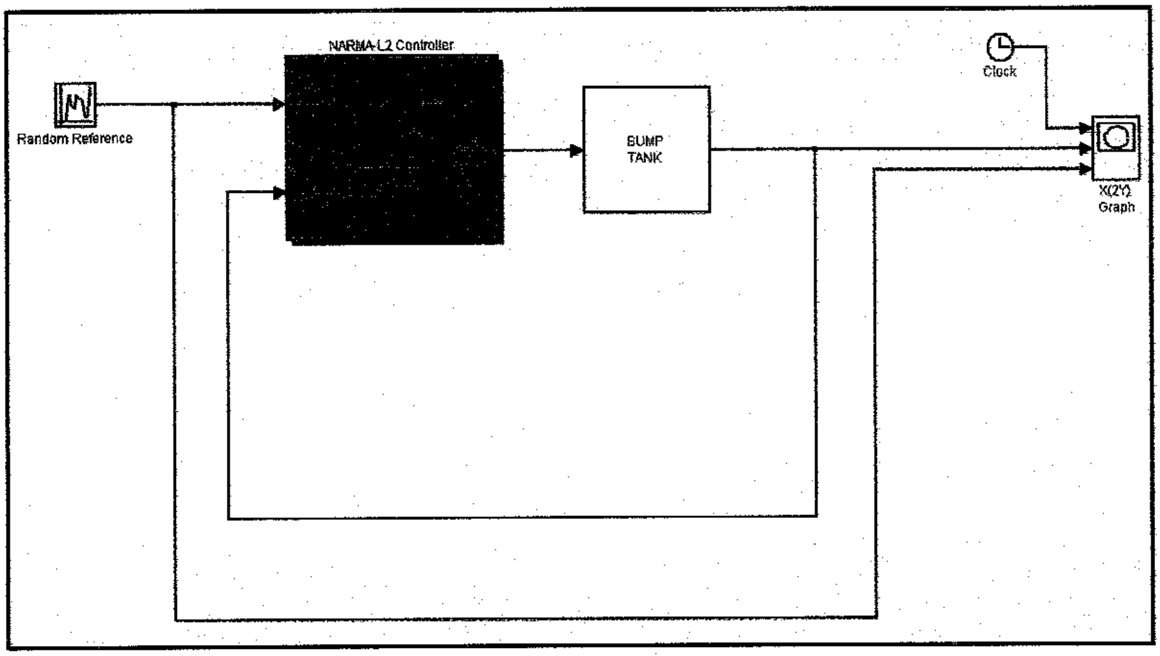

Figure 14: *NARMA-L2 Controller Block Diagram of a Sump Tank*

Figure 11 illustrates one of the Neural Network controller types, which is the NARMA-L2 controller, adapted to the sump system. For this neurocontroller, there are no required PID values. The solids in was varied from 40%, 60%, and finally to 80%. From what can be observed from the results' graphs, the system responded well towards changes in the system but sustained a large number of errors. The magnitudes of the errors are the same for every percentage of solids in to the sump. The results of the simulation using NARMA-L2 controller are as follows, illustrates by Figure 15, 16 and 17.

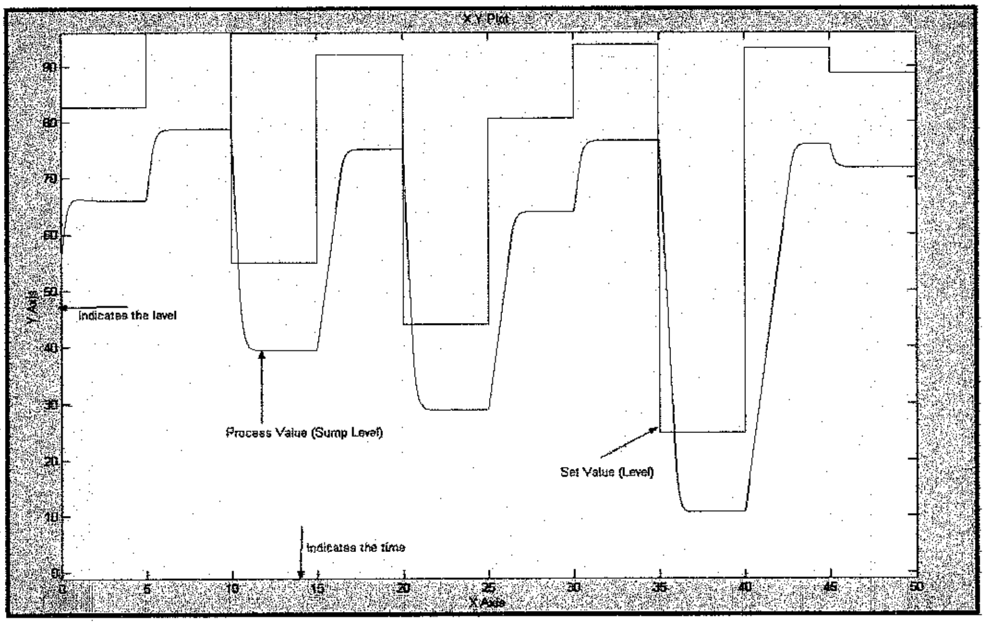

Figure 15: *Result for 40% Solids In*

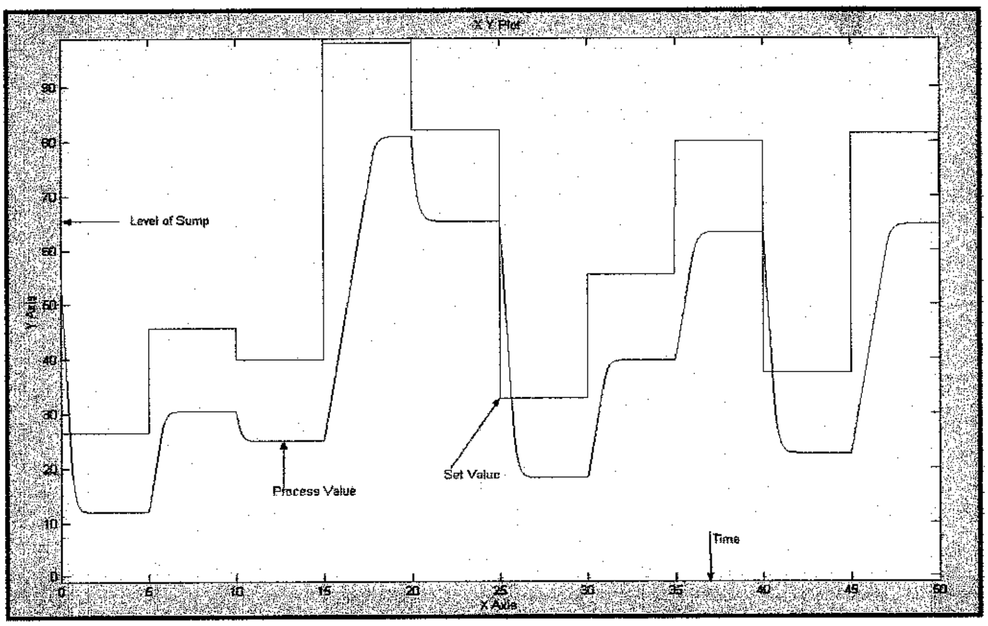

Figure 16: *Result for 60% Solids In*

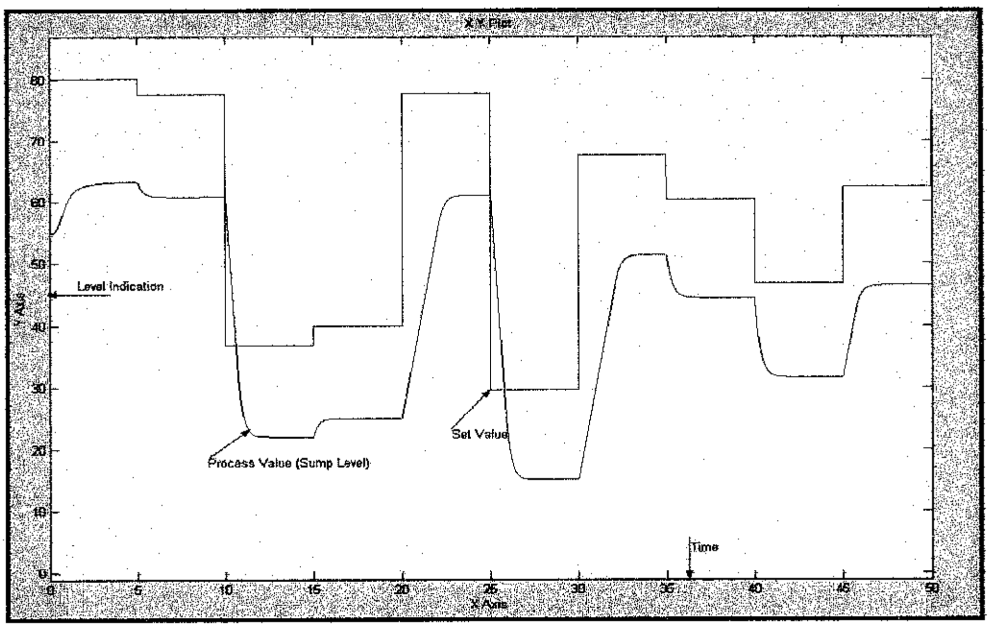

Figure 17: *Result for 80% Solids In*

4.2 Findings Based on the Simulation Done

4.2.1 Feedback and Smith Predictor

The simulation process was done by fixing the sump volume to 50 m^3. The pumping rate is specified at 10 % rate with full opening of the control valve. The process was simulated with a set point change with the step size of 5 % solid flow that has the step size of 5 hours. Throughout the simulation for both Feedback and Smith Predictor Controller Method, the step size and step time is maintained at the same value.

Generally, for all sets of data regardless the controller type, the residence time of solid increased as the amount of solid flow in increased (40%-80%). This has also induced the increment of the total solid and water hold up in the sump tank.

When a set point change was stipulated at t = 5, the system with Smith Predictor Controller Method react vigorously compared to the Feedback Controller. Even though the value shoots up to almost 90 % of the tank level, the process variable still maintained at acceptable region and does not overflow the sump tank.

However, when a small load change was introduced at t = 10 hours, a different behavior can be observed. The process values tend to increase when load change was introduced. The Feedback Controller produces a higher 'overshoot' compared to the Smith Predictor Controller Method. This situation contradicts the earlier situation when there is a set point change introduced. For the Smith Predictor Controller Method, the load changes have small impact to the process value, but the set point have bigger impact to the controller, and vice versa to for the Feedback Controller.

Generally, the tuning result obtained from the literature gave a good result where it manages to meet the main requirement, not to overflow the sump and provide a constant level for the sump.

<u>*Solid 40 %*</u>

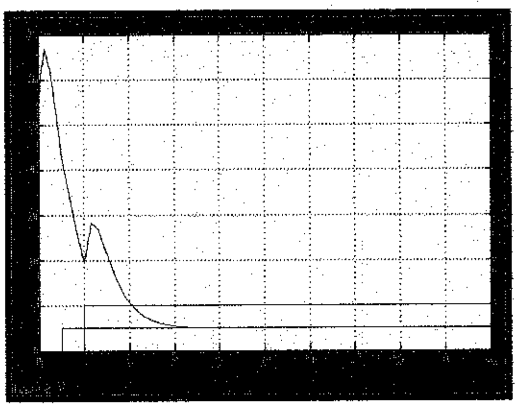

Figure 18: ***Feedback Controller Method***

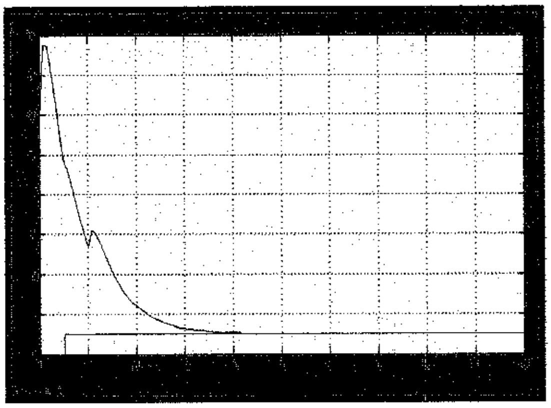

Figure 19: ***Smith Predictor Controller Method***

When the value of the solid flow in is at 40 %, the Feedback controller produces a better response. The settling time of Feedback Controller at this stage is faster than the Smith Predictor Controller Method. The settling time for the Feedback Controller is approximately 30 hours, while the settling time for the system with Smith Predictor Controller Method is at 40 hours.

Solid 60 %

Figure 20: ***Feedback Controller Method***

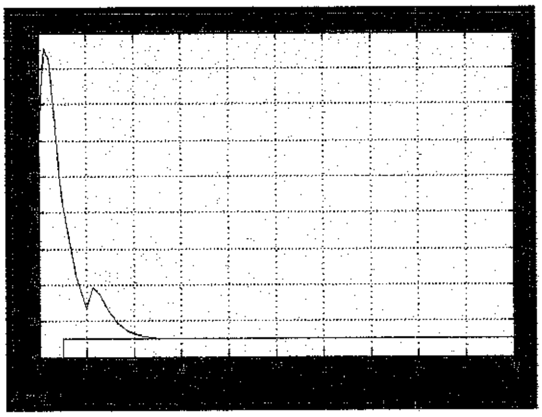

Figure 21: ***Smith Predictor Controller Method***

For the 60 % solid flow in to the sump, the Feedback controller produces a better controlling performance than the Smith Predictor Controller. The controller manage to get the process value to settles at t = 22 hour, while the process value for Smith Predictor Controller only settles at t = 25 hour.

Solid 80 %

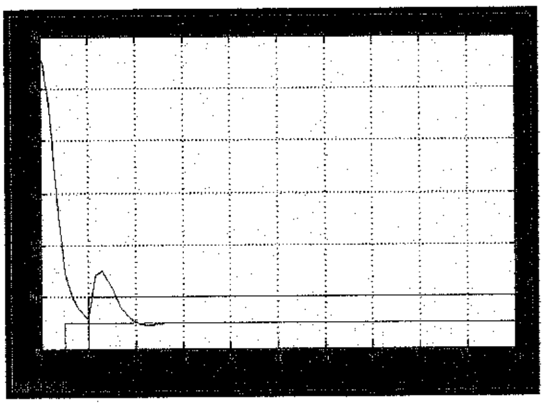

Figure 22: ***Feedback Controller Method***

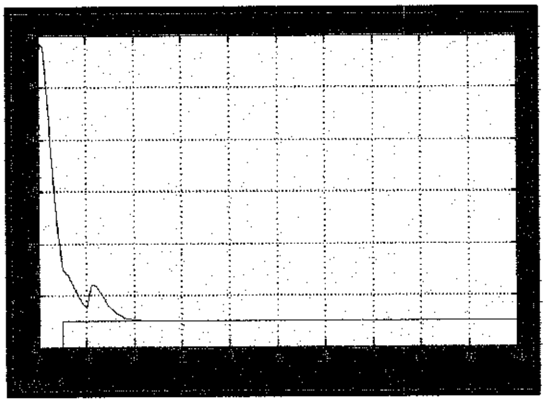

Figure 23: ***Smith Predictor Controller Method***

However, different scenario is exhibit for 80 % of solid flowing in to the sump tank, where the Feedback Controller settles the process values at t = 20. This is somehow identical to the settling time for the Smith Predictor Controller Method. In order to determine the best controller performance, the index of Integral of the absolute value of the error (IAE) is taken into consideration. The IAE at the minimum value is the favorable in order to determine the best controller performance. Obviously the Smith

Predictor Controller Method has the smaller amount of IAE for the 80 % of solid flow. Therefore, it performs better at this stage.

4.2.2 Feedforward Controller

For the feedforward control, same procedures applies, however, additional disturbance was introduce to monitor the performance of this type of controller towards sump system. For the system with 40% solids in, results shows that it performs the best when the value of the controller are at P = 0.9950 and I = 0.1667.

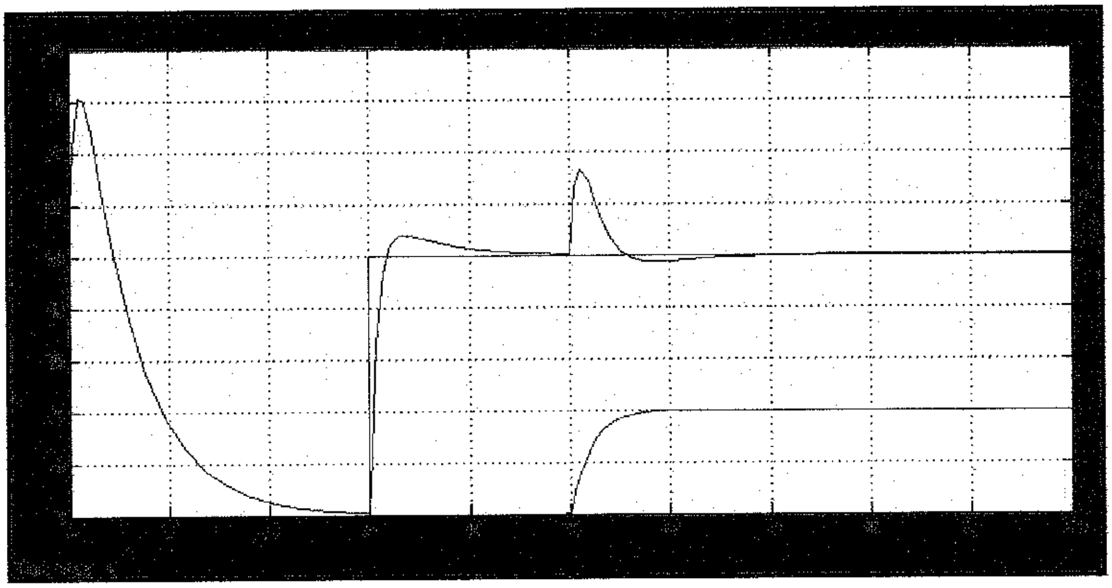

Figure 24: *Tuning Result for Feedforward Controller with Value of P = 0.9950 and I = 0.1667 at 40% Solids In*

There are two disturbances introduced at this stage where the first disturbance is at t = 30 hours and the second disturbance was simulated at t = 50 hours. The controller responded quickly and the overshoot is not too high, therefore leads to a better stability in the process. This is favorable due to the unstability of the sump itself when no controller applied to it.

For 60% of solids in to the sump, Figure 25 illustrates the result, where there is no big different comparing to the result obtained for the value of 40% of solids into the system. The controller responded well at every time where the disturbances were introduced. The settling time is quite fast. However, the settling time is not as fast as the system where the percentage of solids in is at 40%. The error also increase at this stage compare to the first result obtained for the feedforward controller.

Figure 25: *Tuning Result for Feedforward Controller with Value of P = 1.000 and I = 0.1667 at 60% Solids In*

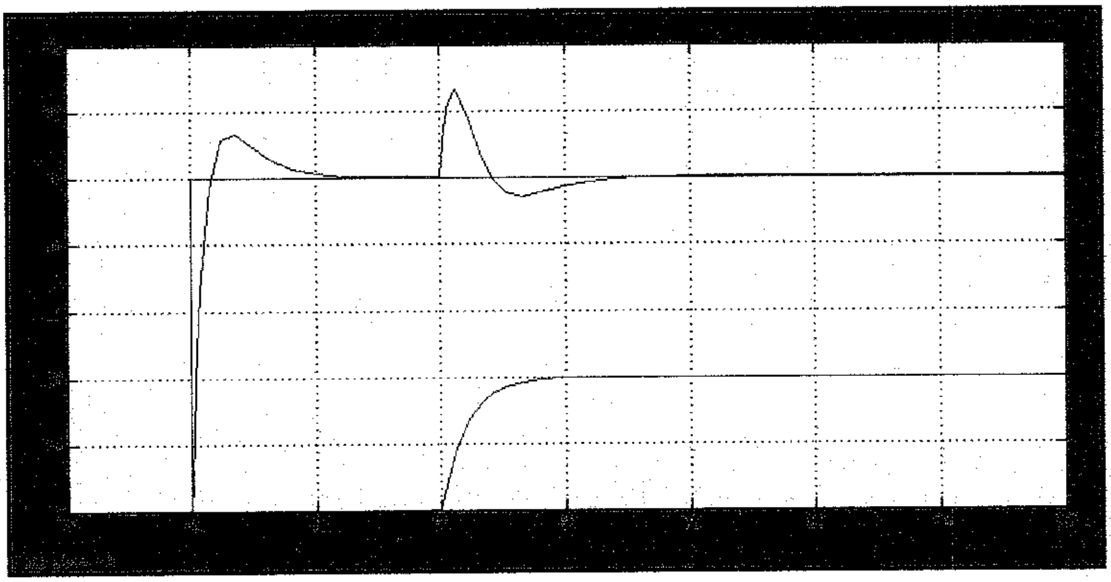

Figure 26: *Tuning Result for Feedforward Controller with Value of P = 1.2520 and I = 0.3571 at 80% Solids In*

Referring to the simulation result for 80% of solids in to the sump (Figure 26), the controller seems to perform the best at this amount of solids in. results shows that when disturbance were introduced at t = 30h, the process settles at t = 40h. This is the fastest rate compare to other two results earlier for this feedforward controller. The consecutive disturbance also results in the process value to settles faster compare to other two earlier results. For the disturbance at t = 50h, the process starts to stables at approximately t = 61h. The result for the feedforward control shows that the controller performs better at the percentage of solids in is at 80%.

4.2.3 Cascade Controller

The tuning result of cascade controller at same amount of solids in is illustrate by figure 25, where the system responded better with the application of this cascade control. In this cascade environment, three disturbances were introduced instead of two in the feedforward control strategy. The time is at t = 5, 30, and 50. At the start of the experiment, a large number of overshoots occurred when the system starts to operate under control. However, the controller manages to overcome the large deficit fast manner. At t = 30 hours however, the system does not respond to the disturbance and maintain its stability, and at t = 60 hours, the disturbance introduced results in a small deviation of the process and the controller manage to settles the process value at fast rate.

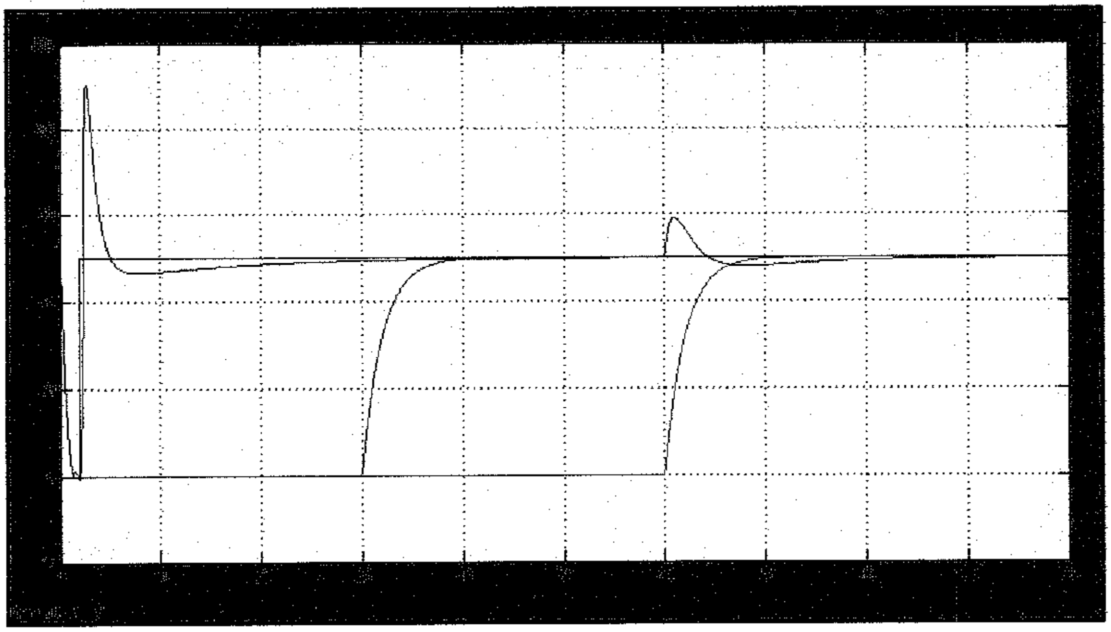

Figure 27: *Tuning Result for Cascade Controller with Value of P = 1.0077 and I = 0.1111 at 40% Solids In*

The result for the other values of solids in are illustrate as follow.

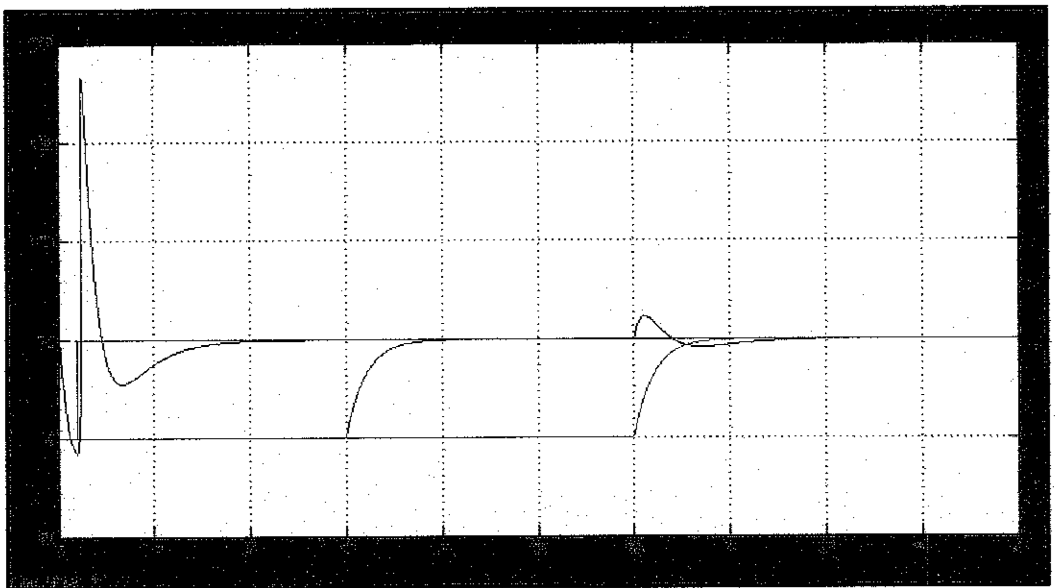

Figure 28: *Tuning Result for Cascade Controller with Value of P = 0.8062 and I = 0.1724 at 60% Solids In*

For this cascade control at the percentage value of 60% of solids, the controller responded well at the disturbances introduces, however, the controller fails to keep the level below 100 and it tends to overflow the system. Even though the settling time is fast, the controller is considered to fails its objective to avoid overflow. Therefore the controller is not suitable for this type of situation.

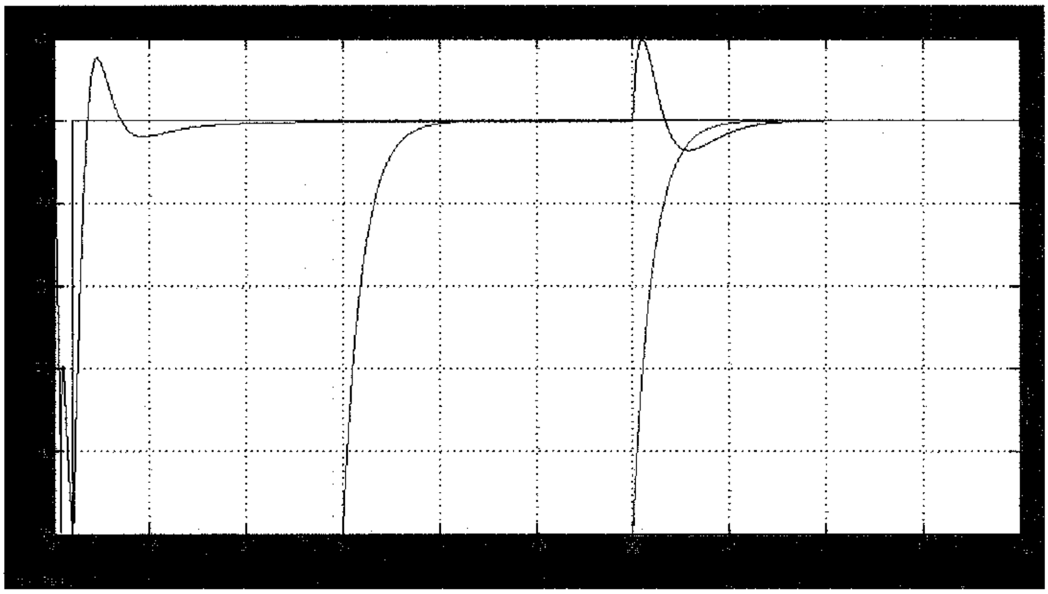

Figure 29: *Tuning Result for Cascade Controller with Value of P = 1.2520 and I = 0.3846 at 80% Solids In*

At 80% of solids in, the controller seems to be at its best performing state, where it manages to keep the level intact. The overshoot after every disturbance is small and the settling time is the fastest in this cascade control compared to the other two results obtained earlier. Therefore, the controller is said to perform the best at 80% of solids flow in to the sump.

4.2.4 Neural Network (NARMA –L2 Controller)

The NARMA-L2 controller is one of the neurocontroller types available in the neural network toolbox in the MATLAB programming. It is also refer to as feedback linearization control. It is referred to as feedback linearization when the plant model has a particular form (companion form). It is referred to as NARMA-L2 control when the plant model can be approximated by the same form. This controller manipulates the concept of transforming nonlinear system dynamics into linear dynamics by canceling the nonlinearities.

From the results obtained from the simulation in the MATLAB shows that there are a big error still occurs even though the performance goal during the network training approached to zero. Referring to Figure 15, 16, and 17 (at the result of the simulation), the process value responded well towards the change in system set value. The level is maintained at specified value but the error is quite big. The error is constant for every percentage of solids in. The error remains at 16 throughout the simulation.

This error can be eliminated by further training of the neural network and manipulating the value of the network architect panel in the plant identification menu. The reason being of the result is that there is no specific method in determining the value. Trial and error is the recommended method. However experience with this type of controller is the best advantage in obtaining the best possible results.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

Several conclusions that reflect the objective of the studies can be made towards the completion of the simulation of the sump system using various controller strategies.

5.1.1 Feedback Controller

For this conventional feedback controller, the system performs the best when the system handles a lower number of solids in to the system.

5.1.2 Smith Predictor Controller

The Smith predictor controller which is an enhancement to the feedback controller, perform vice versa to the feedback, where it is better when handling the higher percentage of solids in.

5.1.3 Feedforward and Cascade Controller

Both type of controller perform the best with handling high amount of solids in to the sump. Both controller have a better efficiency in term of time and overshoot. Comparing both, cascade control manages to minimize error the best and have a faster rate of settling time.

5.1.4 Neural Network (NARMA-L2 Controller)

When the sump system was put under the neurocontroller of NARMA-L2, the result is quite poor due to lack of training of the data and inaccurate trail and error method. The controller responded well towards any change in the system, however the error remain the same for every disturbances introduced.

CHAPTER 6

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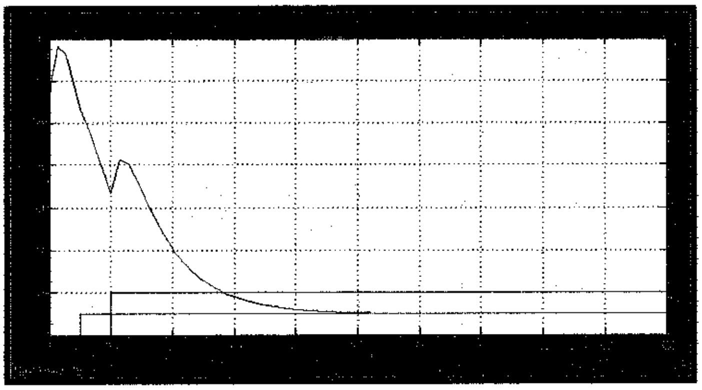
APPENDICES

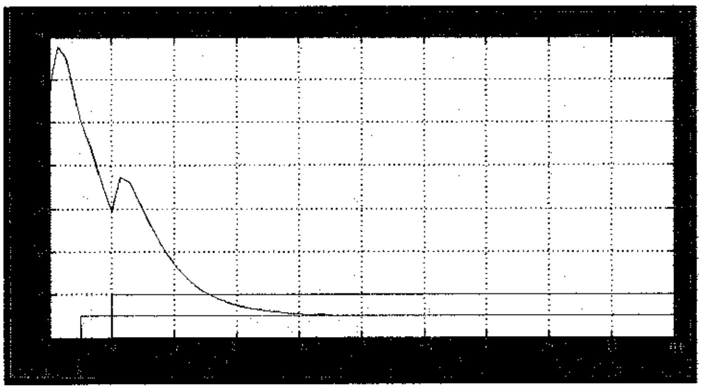
APPENDIX A: Feedback Controller Tuning Results

Tuning result for condition of 40 % of solid flow in:

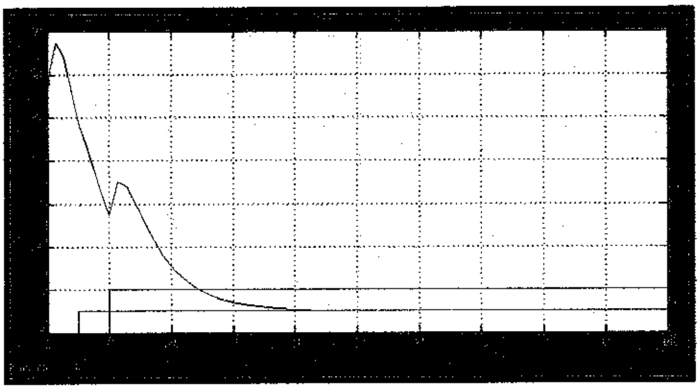
<u>Tuning 1</u> (P = 1.0077, I = 0.1111)



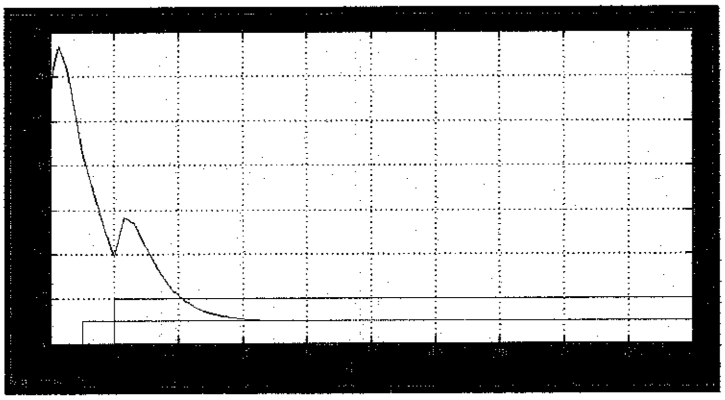
<u>Tuning 2</u> (P = 1.0050, I= 0.1250)



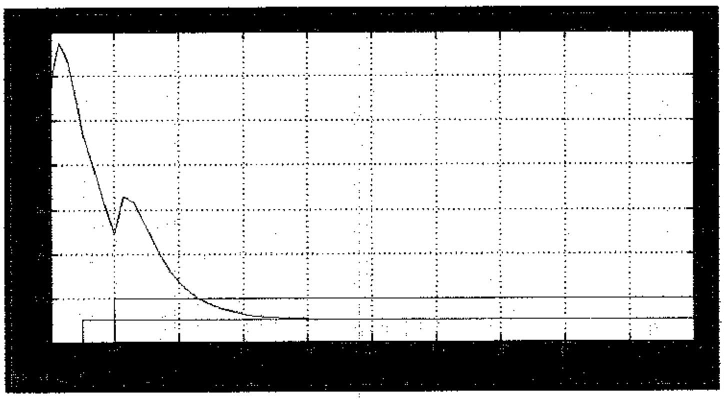
<u>Tuning 3</u> (P = 1.0075, I = 0.1333)



<u>Tuning 4</u> (P = 0.9950, I = 0.1667)

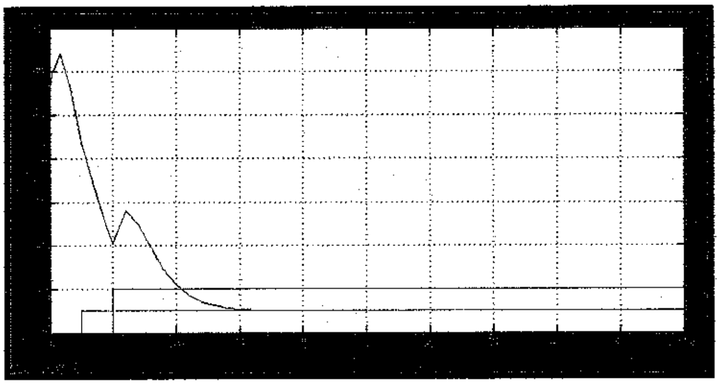


<u>Tuning 5</u> (P = 1.0002, I = 0.1429)

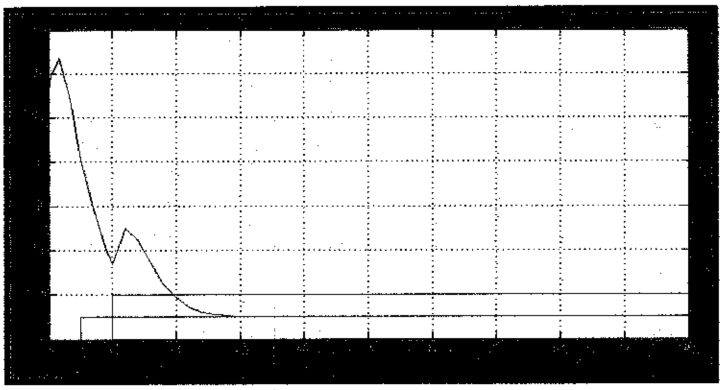


Tuning result for condition of 60 % of solid flow in:

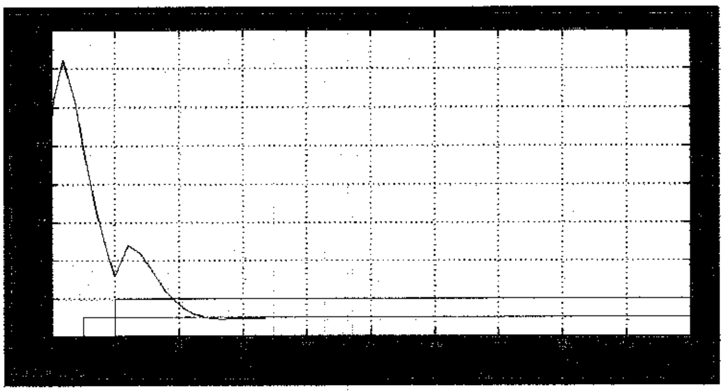
Tuning 1 (P = 1.0000, I = 0.1667)



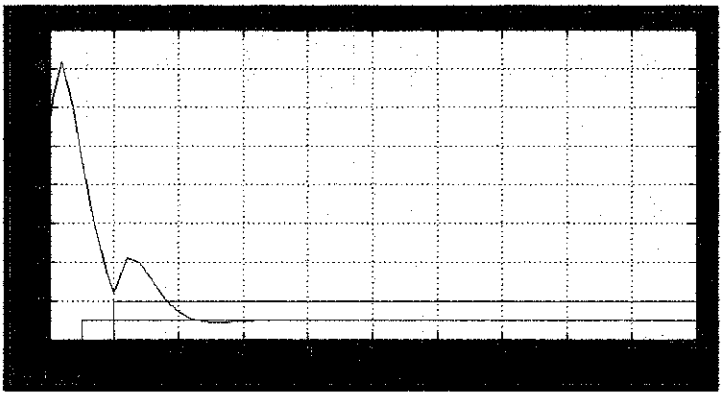
Tuning 2 (P = 0.9949, I = 0.1852)



Tuning 3 (P = 0.8062, I = 0.1724)

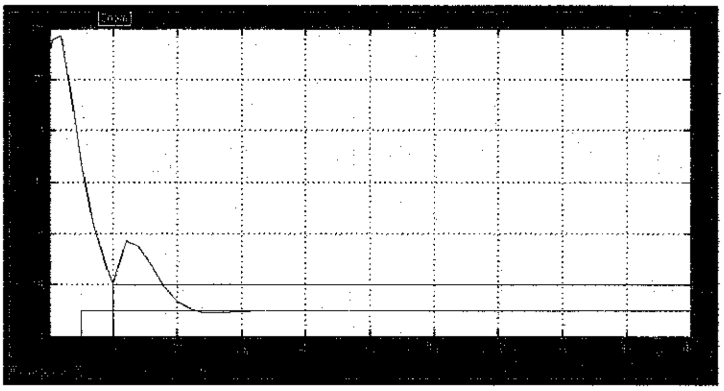


Tuning 4 (P = 0.8021, I = 0.1887)

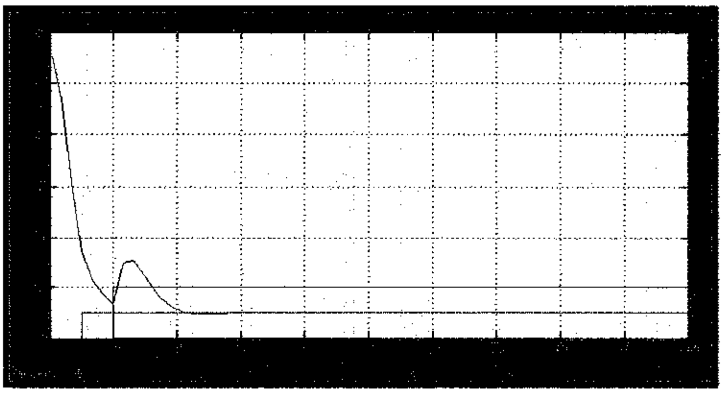


Tuning result for condition of 80 % of solid flow in:

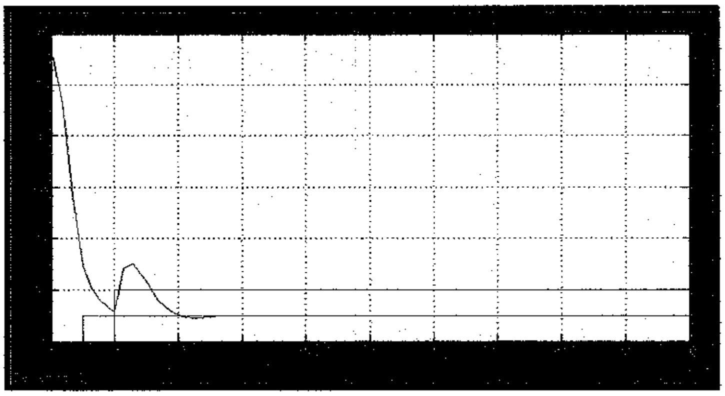
Tuning 1 (P = 1.0000, I = 0.2381)



Tuning 2 (P = 1.2533, I = 0.3571)



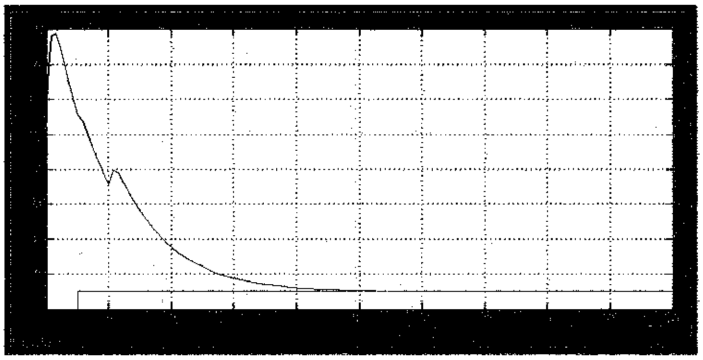
Tuning 3 (P = 1.2520, I = 0.3846)



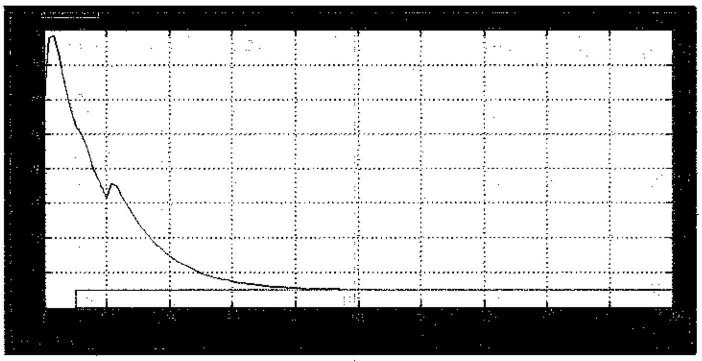
APPENDIX B: Smith Predictor Controller Tuning Results

Tuning result for condition of 40 % of solid flow in:

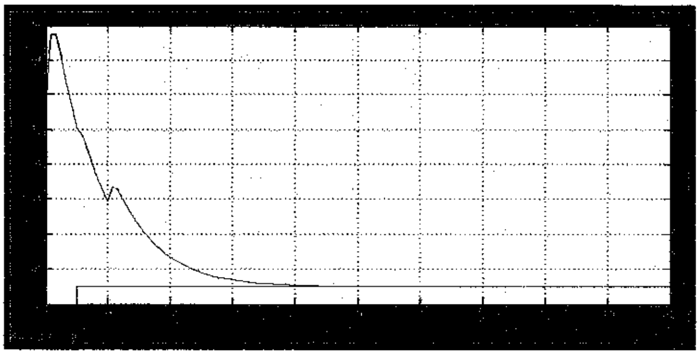
Tuning 1 (P = 1.0077, I = 0.1111)



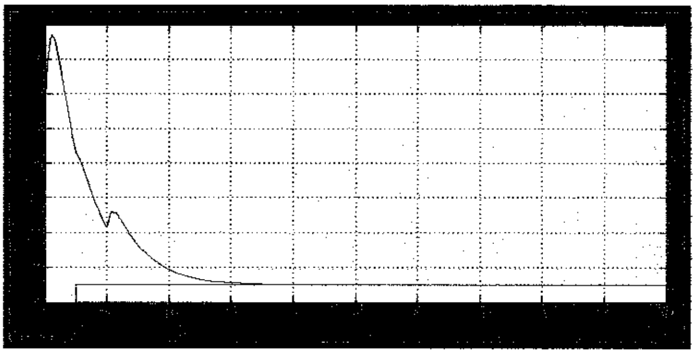
Tuning 2 (P = 1.0050, I= 0.1250)



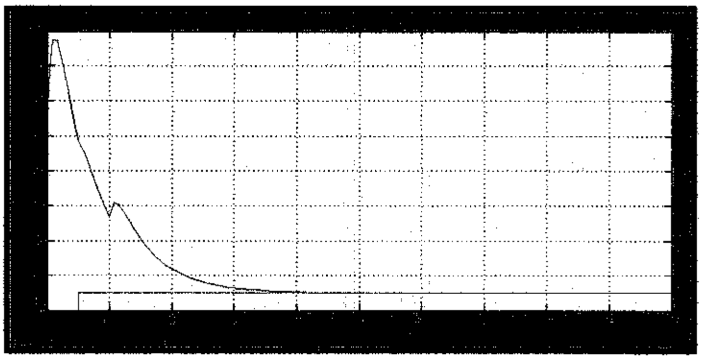
Tuning 3 (P = 1.0075, I = 0.1333)



Tuning 4 (P = 0.9950, I = 0.1667)

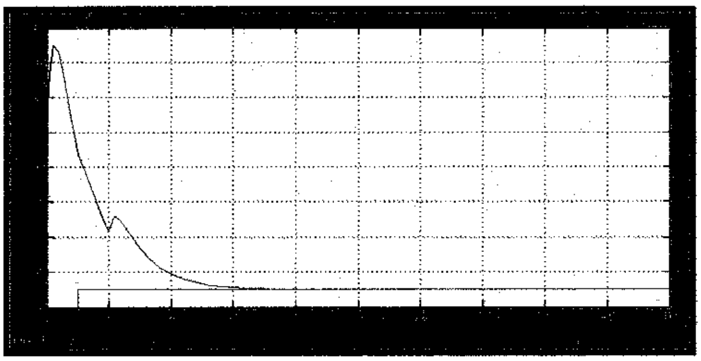


Tuning 5 (P = 1.0002, I = 0.1429)

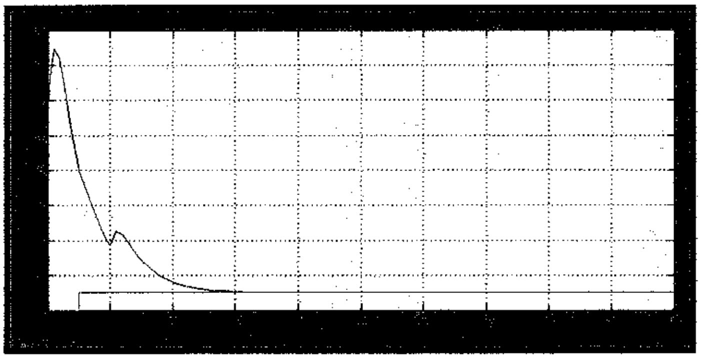


Tuning result for condition of 60 % of solid flow in:

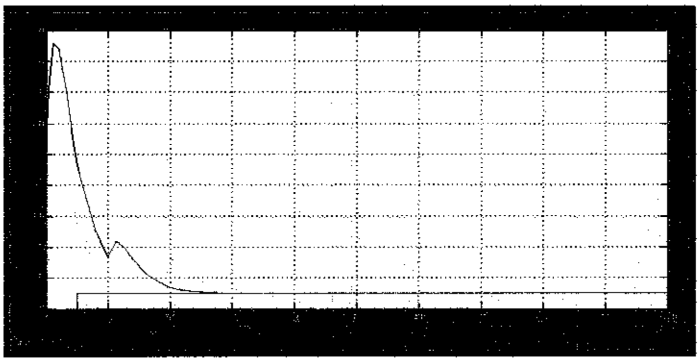
Tuning 1 (P = 1.0000, I = 0.1667)



Tuning 2 (P = 0.9949, I = 0.1852)

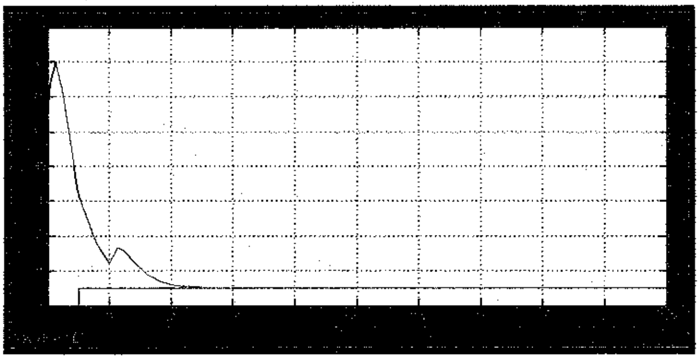


Tuning 3 (P = 0.8062, I = 0.1724)

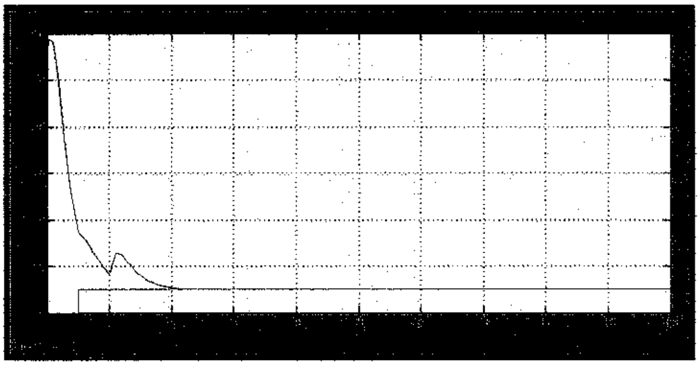


Tuning result for condition of 80 % of solid flow in:

Tuning 1 (P = 1.0000, I = 0.2381)



Tuning 2 (P = 1.2533, I = 0.3571)



Tuning 3 (P = 1.2520, I = 0.3846)