IMPLEMENTATION OF NEURAL NETWORK PREDICTIVE CONTROLLER FOR A SUPERSONIC SEPARATOR

By

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DISSERTATION

Submitted to the Electrical & Electronics Engineering Programme
in Partial Fulfillment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
(Electrical & Electronics Engineering)

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CERTIFICATION OF APPROVAL

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TRONOH, PERAK

December 2010

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 acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

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Nurmelissa Suraya Md Ridzuan

ABSTRACT

This project is to perform a controller for a gas dehydration unit called Supersonic Separator. The previous works have achieved physical system design and determined the best control strategy for the process. The calculations were made at desired measuring points to produce the control zone pressure profile. It was observed that the system needs a controller which able to handle the non-linear properties and increase the stability of the system and efficiency of the process. A Neural Network Controller was recommended to be a better alternative. Therefore, the research continued by implementing a modeling process for the system. The input/output data obtained previously were trained with different algorithms in order to implement a suitable configuration for the Neural Network Predictive Controller. By the end of this research, it is proven that a Neural Network Predictive Controller is able to keep the system in the desired operating region and reduce the ripples on the output therefore increasing the stability of the system.

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LIST OF ABBREVIATIONS

CFD	Computational Fluid Dynamics
CV	Controlled Variable
FYP	Final Year Project
MPC	Model Predictive Control
MV	Manipulated Variable
NGL	Natural Gas Liquids
NN	Neural Network
PID	Proportional Integral Derivative
PRC	Process Reaction Curve
TEG	Triethylene Glycol
SISO	Single Input Single Output

CHAPTER 1
INTRODUCTION

1.1 Background of Study

Natural Gas has been discovered as an optional energy resource centuries ago [1]. In order to be used in industries, the practitioners have been trying to approach methods to separate water vapor from the gas mixtures. Throughout the decades even until now, there is only chemical approach for the dehydration process. Twister BV is an invention applying supersonic velocities to produce gas and extracting water as well as hydrocarbon liquids. It was the first introduced in 2004 on Shell Sarawak's B-11 offshore platform as a non-chemical process which reduced the exposure to hazardous gas [2],[3]. The current controller used for this dehydration unit is based on PID algorithm approach. However, there are some disadvantages in terms of stability by using PID controller. Thus, this research concentrates on applying Neural Network Predictive Controller at the downstream of the Supersonic Separator to have a better control in relationship of input and output based on the data obtained from previous project entitled "Pressure Controller of a Chemical-Free Gas Dehydration Unit".

1.2 Problem Statement

It is approved that supersonic separator has become more reliable invention for gas dehydration compare to conventional method using Triethylene Glycol (TEG) due to non-chemical process. However, rapid expansion of moist air or steam in supersonic separator would cause unstable shockwaves and disturbance in flow. Despite of that, the response of current PID algorithm controller used would create fluctuates in dynamic condition which effect the system to swing out of stability and its linearity. Thus, Neural Network Predictive controller is proposed as it able to estimate future plant output and obtained optimum control input to reduce error.

1.3 Objectives and Scopes of Study

The main objectives of this project are:

1) To obtain a system model by revalidating the data of a supersonic separator model.

2) To design a suitable predictive controller based on Neural Network approach for the system.

3) To analyze the Neural Network predictive controller compatibility to operate on fluid dynamics condition.

The scope of study consists of validation and simulation of the supersonic separator model using MATLAB software as well as designing the controller. The study is implemented in two parts where the first part consists of study on supersonic separator and data validation using MATLAB. The second part is to study on the Neural Network and to determine the suitable method to implement the controller on supersonic separator. Some of the characteristics will come into consideration such as transient response and steady state response during the simulation. The control performance of the designed controller will be observed.

CHAPTER 2
LITERATURE REVIEW

2.1 Supersonic Separator

Natural gas extracted in the fields consists of a combination of substances which 90% is methane and the other 10% consists of ethane, propane, and heavier hydrocarbons, water and, possibly, hydrogen sulfide [1]. The separation process of the natural gas into components consists in cooling the flow to desired values of condensation temperature.

A team of Russian scientists suggested using adiabatic cooling in combination with the Joule–Thomson effect for separating various components from the main flow of natural gas [4]. This method known as Super Sonic Separator or 3S. Due to the centrifugal forces, the swirled flow of the natural gas at the subsonic area which then accelerated to the supersonic velocities will be able to separate the condensed droplets of one or another target component. A physical extraction can be used to implement the separation process in the nozzle due to the lower static temperature of gas compared to the condensation temperature.

For Twister, the equipments used are less since the process of dehydration, dewpoint and recover NGL can be done simultaneously despite of the operating pressure. Operation feedback to date has demonstrated zero downtime, which means fewer spares and lower capital expenditures [2].

2.1.1 Shockwave

The surfaces of abrupt change in fluid properties are called shock waves or shock fronts. Measurements of fluid density, pressure, and temperature across the surfaces always increase along the direction of flow, and that the rates of change are usually so rapid as to be beyond the spatial resolution of most instruments. Shock waves in supersonic flow may be classified as normal or oblique according to whether the orientation of the surface of abrupt change is perpendicular or at an angle to the direction of flow [5],[6].

Figure 1 shows the ideal fluid dynamics in the controller design. The focused variable will be the pressure ratio which determines the position of the shockwaves in the sonic nozzle. The shockwaves must be between the liquid re-evaporation zone. If it reaches the shock front, the liquid will re-vaporize into dry gas as it is too far from the separation point. If the shockwaves reach the separation point, the liquid will not fully condensed and decreasing the quality.

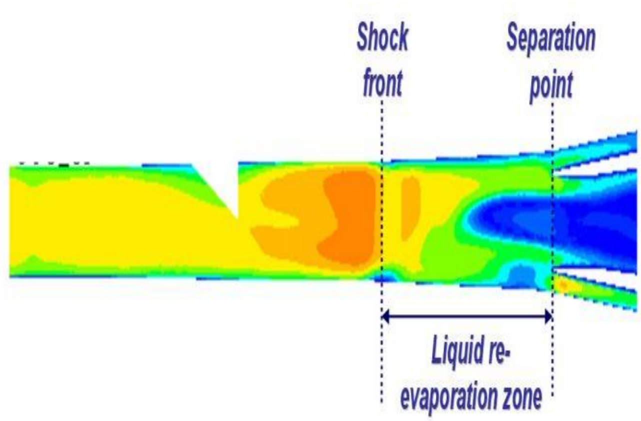

Figure 1 : Fluid dynamics analysis on gas dehydration unit [7].

Blue region shows the area with the least pressure level while Orange region shows the area with the highest pressure level.

Shock waves occurred from sharp and violent disturbances generated from a lightning strike, bomb blast, or other form of intense explosion, and from steady supersonic flow over bodies. It was suggested that the presence of shockwave prevents the gas from expanding to such extend that the temperature in the region of extraction would turn out to be low enough for the condensation of components of interest [4].

2.2 Neural Network

In a shock wave the properties of the fluid (density, pressure, temperature, velocity, Mach number) change almost instantaneously. Neural network is best implemented on where the volume, number of variables or the data vary significantly. This controller works on a learning principle where it will constantly iterate the function based on the given input to match the given output. In gas dehydration process, the artificial neural networks (ANN's) are used for modeling, identification and control of unknown nonlinear plants.

In process control, ANN was applied through adaptive control or model-based control [8]. ANN could be use to regulate controller for optimal performance in on-line monitoring process data. Besides that, ANN also applicable as estimator in advanced control techniques for the dynamic modeling process variables.

2.2.1 Neural Network Architecture

Neural Networks consist of number of interconnected processing elements or neurons. The structure of the network is determined by the arrangement of the inter-neuron connections and the nature of the connections. The selection of learning algorithm on how to train the connection is important to achieve a desired overall behavior of the network. The Backpropagation algorithm is the most widely used of learning algorithms. There are two network topologies which are Feedforward Neural Network (FNN) and Recurrent Neural Network (RNN) or feedback network [9],[10].

Neural network can also be integrated with other type of controller such as PID as shown by [11]. It is easier to implement and can improve the controller performance. This eliminates the need to tune the PID parameters that would take a lot of time every time the process characteristic change. Furthermore, the research shows that a four layer neural network is highly independent as the last layer will be able to tune itself. However, in this research, a simpler way is implemented using a Feed-forward Back Propagation network with two hidden layers.

2.2.2 Neural Network Predictive Controller

Model Predictive Control (MPC) is widely used due to its characteristic that able to predict the future behavior of a plant. MPC allows the controller to deal with an exact model of the real process dynamics thus increasing the control quality. Despite of that, MPC algorithms consider plant behavior over a future horizon in time. The feedforward and feedback disturbances application make it possible to obtain process output close to the desired trajectory. By using computational methods, minimization of cost function is one of the characteristic that implies in most of the nonlinear predictive control algorithms in order to obtain optimal command for any process.

Based on the study Mahdijalili and Araabi [12], MPC is proposed for a heat exchanger nonlinear process. It is rather impossible to compute for a system associated with flow and heat transfer due to the large phenomena such as non-uniform local heat transfer rates and fluid temperatures. Thus, this research is focused on the performance of the proposed neural network based predictive controller and compared it with Generalized Predictive Control, which the former leads to better performance. The closed loop system with neural network based control action performs much better than GPC and the output temperature can track the set point values better.

CHAPTER 3
METHODOLOGY

3.1 Procedures and Identification

Based on previous works objectives, analysis on fluid dynamics is fundamental to determine the variables that need to be controlled based on dewpoint and NGL formation temperature. Dimension and sizing of the gas dehydration unit have been determined from the analysis based on the specific active well, Shell B-11 platform as it is an active gas producing platform.. The operating region of the process has been defined by the maximum and minimum pressure that allows physical separation. The input/output data was imported into Matlab for system construction and training.

For this research, the sampling time for the analysis has been assumed in order to build and evaluate linear models of dynamic systems from measured input-output data. The previous collected data will be merged with the evaluation to obtain the parameters needed for further action in designing controller.

Based on the variables that have been determined in fluid dynamics analysis, a Neural Network pressure controller will be built using Matlab/Simulink. The controller would control the variables in order for the physical separation to be possible. This involves the control valves reaction to control the pressure ratio due to increasing or decreasing of feed gas pressure. Simulation and analysis of the system using Matlab/Simulink will be made to analyze and characterize the controllability and stability of the system. The end results will be compared with an existing gas dehydration package.

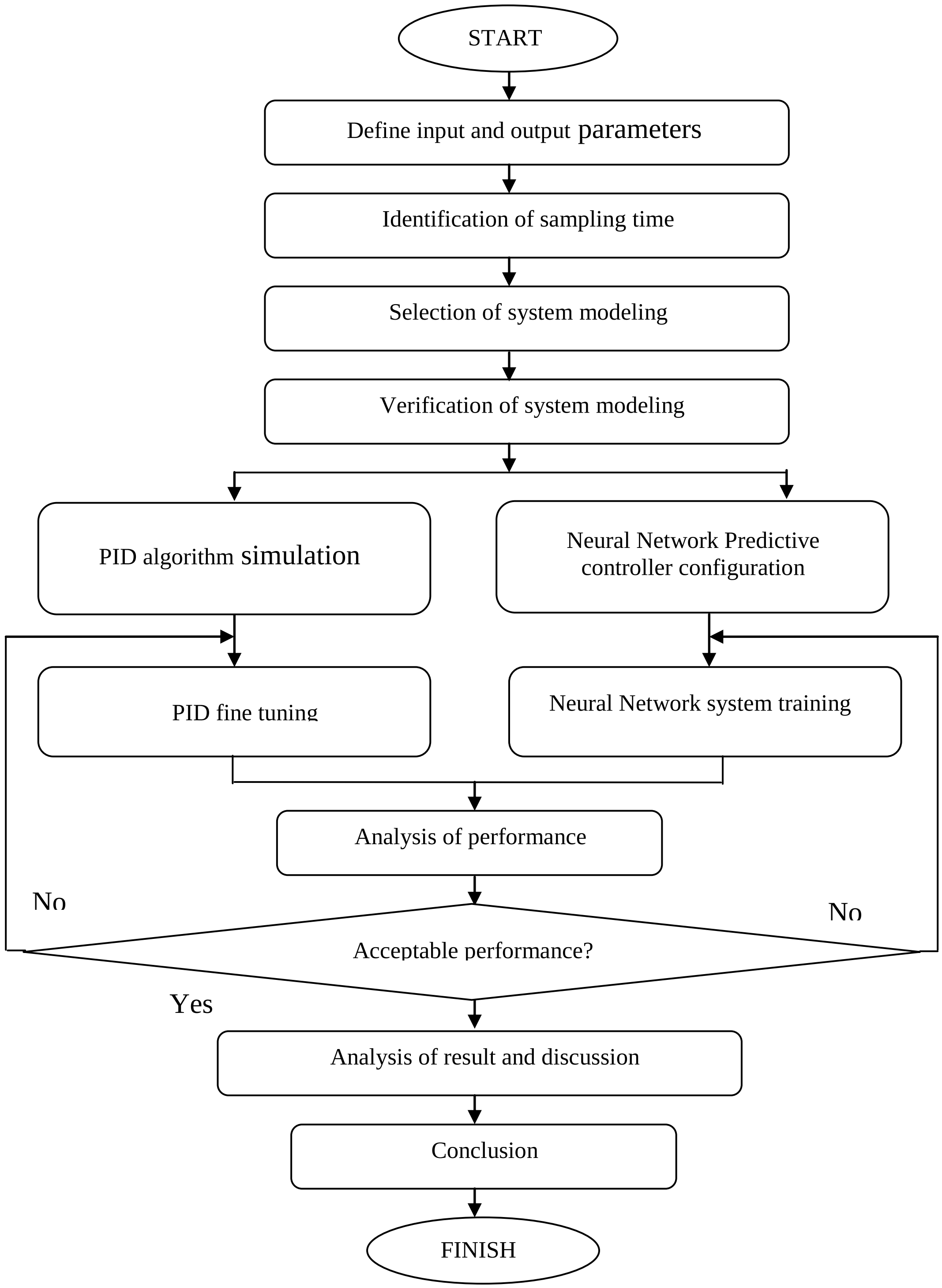

Figure 3 : Project Flow Chart

3.2 Control strategy

The position of shockwave is varied by manipulation of the swirling velocity. This can be done by controlling the flow rate of the stream as it has causal effects with the fluid velocity. Therefore, a control valve is introduced on the downstream side of the system to provide this manipulation.

The control strategy which successfully obtained from previous work is described graphically in **Figure 2**. Neural Network Controller was selected due to its predictive characteristic that enables it to predict the position of shockwave based on a feedforward and feedback back propagation system. In this case, the readings from the three pressure transmitters; P0, P1 and P2 are feedforwarded into the system to become as the input. The valve is assigned as the Manipulated Variable (MV) which will be manipulated the ratio between the input pressures. This ratio is the fundamental to determine the shockwave position. The shockwave position is assigned as the Controlled Variable (CV) which need to be controlled to be within the control zone ; 0.95m to 1m from the sonic throat in order to have complete condensation process.

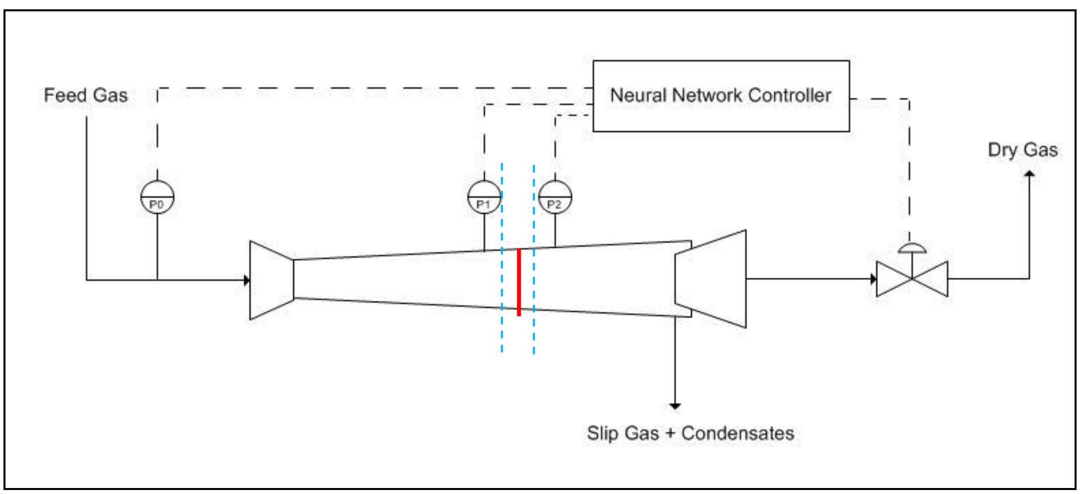

Figure 2 : Control Strategy

3.3 Model Simulation and Validation

In this research, one of the processes is to estimate a model of a system based on the observed input-output data. Several ways to describe a system and to estimate such descriptions exist in Matlab R2007a System Identification. This section provides a brief account of the most important approaches [13]. These are the procedures on selecting the best model structures:

1) Import the collected input-output data from the process to be identified.
2) Examine the data by removing trends and outliers, and select useful portions of the original data.
3) Select and define a model structure.
4) Compute the best model in the model structure according to the input-output data and a given criterion for goodness of fit.
5) Examine the properties of the model obtained.
6) If the model does not achieve the desired response, the data should be revalidated using another model structure.

3.3.1 Import Time-Domain Data into MATLAB

Time-domain data consists of one or more input variables *u(t)* and one or more output variables *y(t)*, sampled as a function of time. Time-domain data have to be imported into the MATLAB workspace as the following variables in **Table 1** and **Figure 4** [13]:

Table 1 : Time-domain data

Parameters	**Description**	**System Identification Variable**
Input	MATLAB variable name or a MATLAB expression that represents the input data. The expression must evaluate to a column vector or matrix.	*VP: Valve opening (%)*
Output	MATLAB variable name or a MATLAB expression that represents the output data. The expression must evaluate to a column vector or matrix.	*Y1: Shockwave position(meter)*
Data name	Name of the data set, which appears in the System Identification Tool window after the import operation is completed.	*mydata*
Starting time	Starting value of the time axis for time plots.	*1sec*
Sampling interval	Actual sampling interval in the experiment.	*0.08sec*

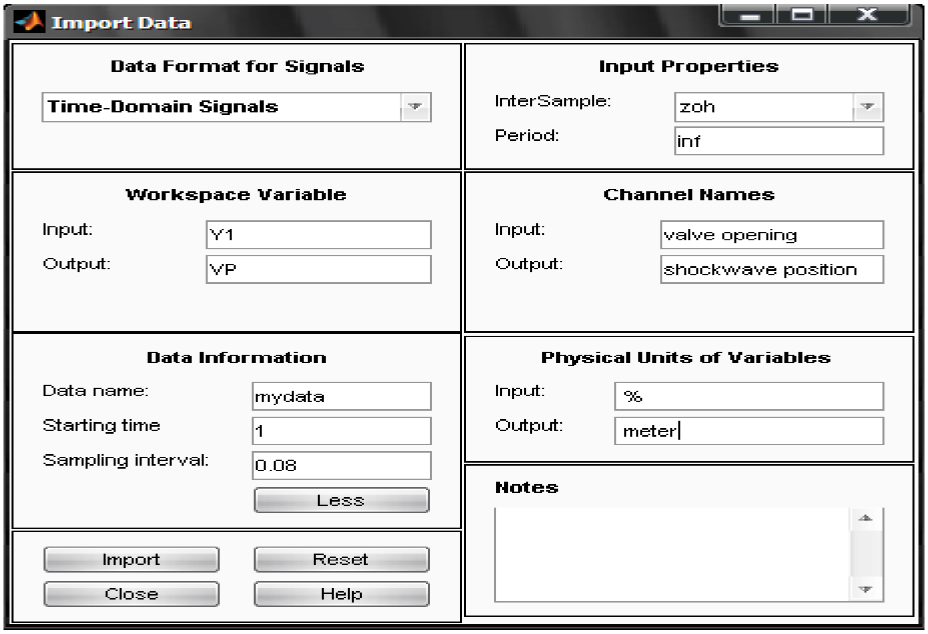

Figure 4 : Import Data in *ident*

3.3.2 Specify Estimation and Validation Data

Different data sets were used to estimate and validate model for best validation results. In the System Identification Tool GUI, *Working Data* refers to estimation data. Similarly, *Validation Data* refers to the data set used to validate a model as in **Figure 5**.

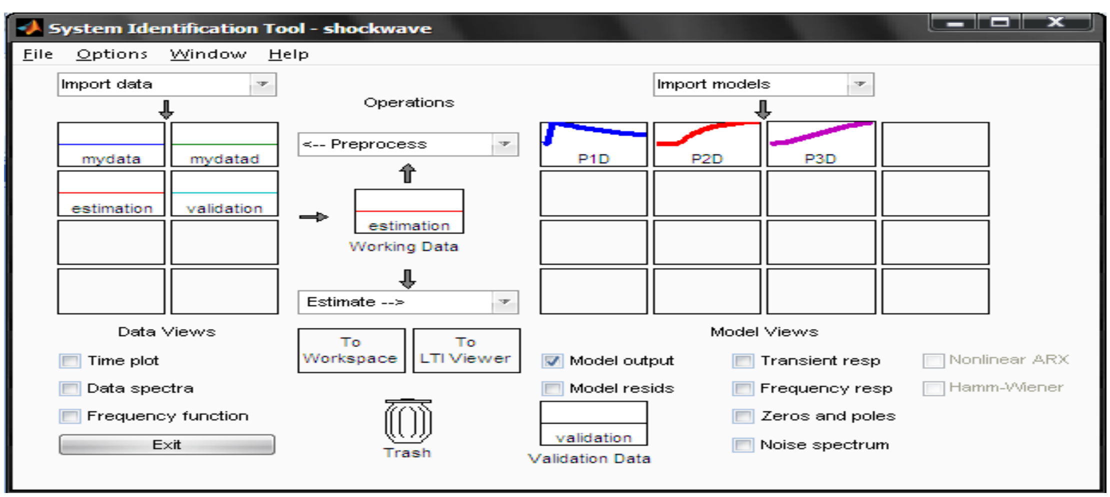

Figure 5: Properties in *ident*

Different data sets were used to estimate (*Working Data)* and validate (*Validation Data)* model for best validation results. The range for the estimation data was set from sample 1 until samples 700 while the samples 701 until 1100 were set for validation data as in **Figure 6**.

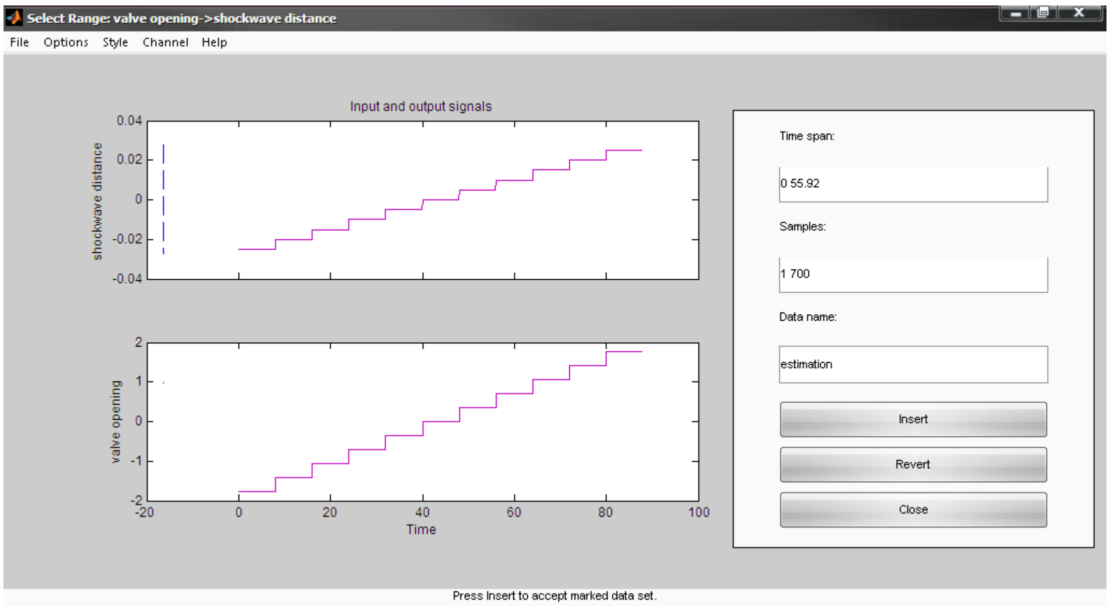

Figure 6: Select Range

3.3.3 Selection of Model Structure.

There are few selections on model structure. In this research, Process Model was selected. **Figure 7** shows the configuration windows to estimate the model using Process Model.

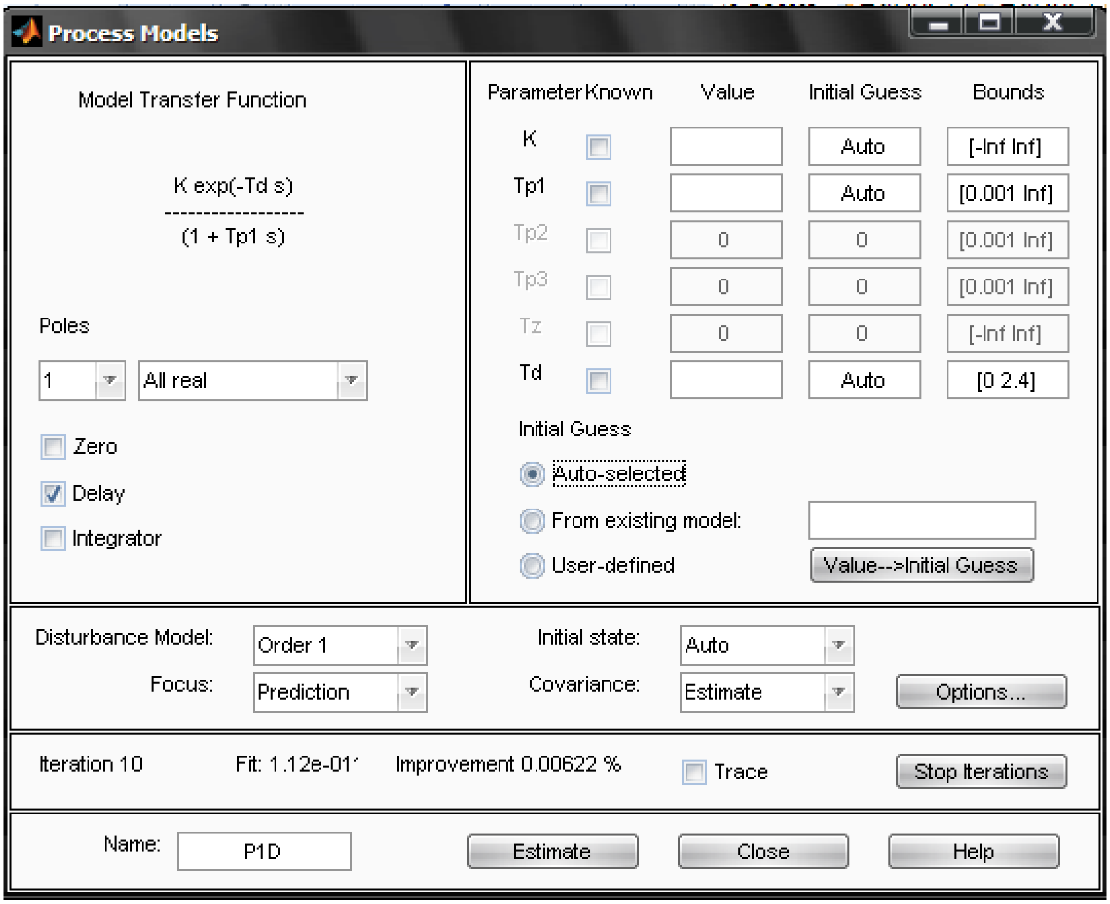

Figure 7 : Process Model Configuration

3.3.4 *Model Output*

The plot takes somewhat different forms depending on the character of the validation data. This could be either time domain data, frequency domain data or frequency function data. In this project, the concern is on time domain data.

One of the important characteristic for selecting the best modeling techniques is by comparing the percentage of the output variations which is the percentage of comparison between the model output with the measured output. A higher number means a better model. A higher number means a better model. The precise definition of the fit is:

$$\mathrm{FIT} = \left[1 - \frac{\mathrm{NORM}(Y - \hat{Y})}{\mathrm{NORM}(Y - \mathrm{MEAN}(Y))}\right] * 100 \qquad \text{(Eq. 1)}$$

where Y is the measured output and $\hat{Y}$ is the simulated/predicted model output.

Multiple sampling times have been tested in order to get the best fits for this process to ensure it could handle the high pressure fluctuations and further increasing the stability of the system.

3.3.5 Analyze Estimated Data

Some characteristics need to be counted into considerations which are the step response and the transient response. Based on that, parameters such as rise time, Tr, and settling time, Ts, also need to be observed.

3.4 PID Controller Tuning

The system response will be tuning using PID algorithm by adjusting the feedback controller parameters to obtain a specified closed loop response. There are two types of tuning and the type that will be used in this system is open-loop or step testing tuning methods utilizes model parameters obtained through empirical modeling [14]. In PID algorithm, there are there modes involved which are:

- Proportional- To ensure controller reduce the response error
- Integral- To ensure controller achieves zero offset
- Derivative- To ensure controller create faster response

The concern parameters for PID tuning are Proportional gain, Kc, Integral time, Ti, and Derivative time, Td. The mathematical PID controller equation is:

$$E(t) = SP(t) - CV(t) \qquad \text{(Eq. 2)}$$

$$MV(t) = K_c \left[E(t) + \frac{1}{T_i} \int_0^{\infty} E(t')dt' + T_d \frac{d\, CV(t)}{dt} \right] + I \qquad \text{(Eq. 3)}$$

3.5 Neural Network Predictive Controller Design

3.5.1 Neural Network Predictive Controller Scheme

Figure 8 shows the general scheme on how Neural Network Predictive controller works with the plant on predicting the future system response. The controller consists of *Optimization* block and *Neural Network Model* block. Firstly, the *Optimization* block will check desired response,y_r, to determine the control signal that minimized the cost function. The control signal,u, become the input for the *Supersonic Separator*. Then, the exact plant response,y_p, being feedback into *Neural Network Model* for future prediction. The predicted plant response from the Neural Network Model,y_m, being compare with the desired response.

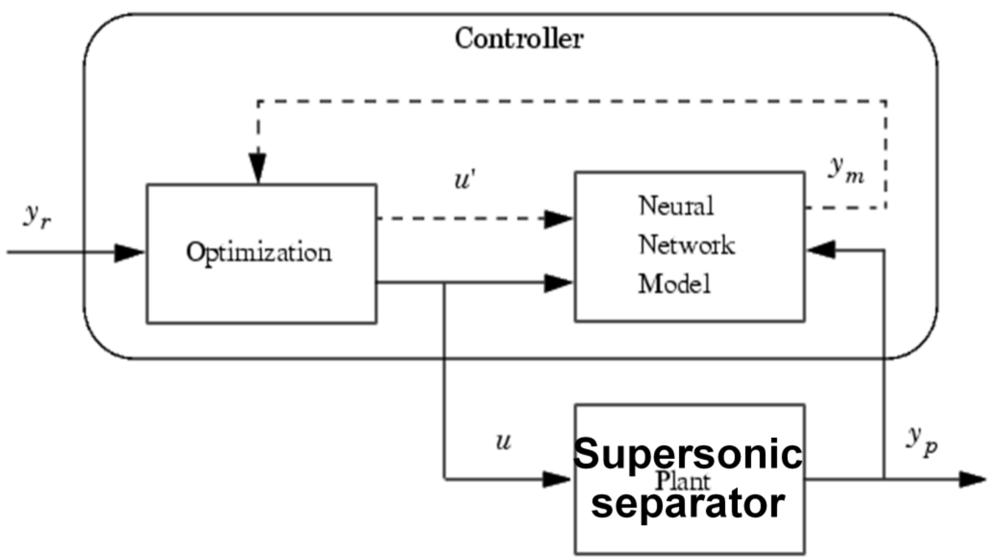

Figure 8 : The Scheme of Neural Network Based Predictive Control.

The cost function is minimized in order to obtain the optimum control input to be applied in the nonlinear plant. The following equation is the mathematical equation for cost function. The first term is to measure errors between predicted and desired output while the second term is penalize excessive movement in Controlled Variable.

$$\boxed{\sum_{j=N_1}^{N_2}(y_r(t+j)-y_m(t+j))^2}+\boxed{\rho\sum_{j=1}^{N_u}(u'(t+j-1)-u'(t+j-2))}$$

with the following requirements

$$\Delta u(k+j-1)=0 \qquad 1 \leq N_u < j \leq N_2 \qquad \text{(Eq. 4)}$$

3.5.2 Neural Network Predictive Controller Simulink Simulation

Figure 9 shows on how the control scheme implemented in Simulink which consists of *Random Reference* block, *Neural Network Predictive Controller* block, *Transfer Function* block and *Scope*. The *Control Signal* of *Neural Network Predictive Controller* function block was connected to the input of the plant model. The output of the plant model was connected to the *Plant Output* to give the feedback behavior.

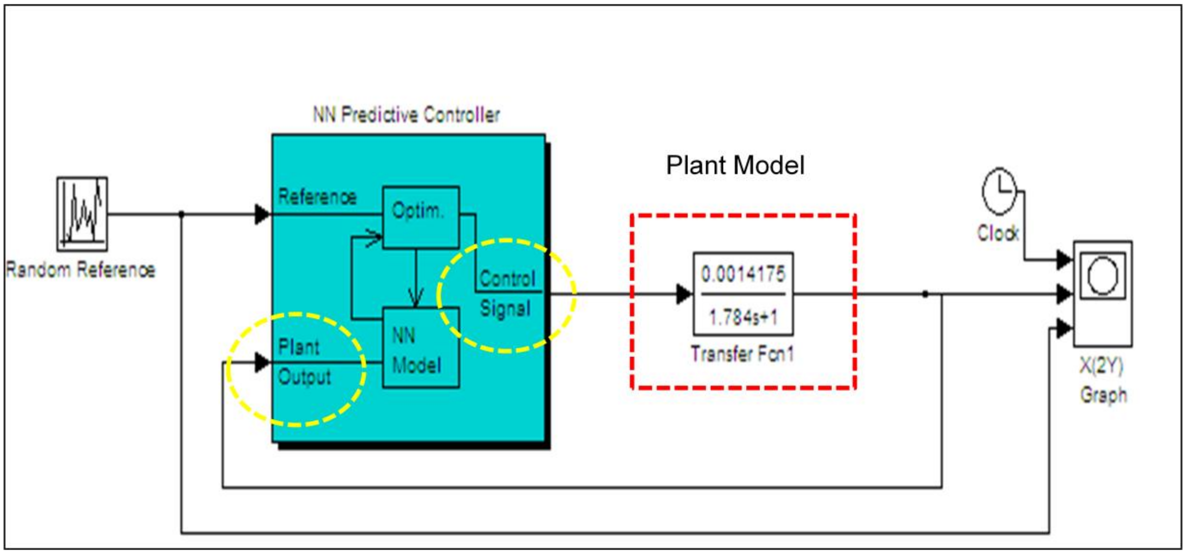

Figure 9 : The Overall System with NN Predictive Controller Block Diagram

This research used neural network with a 3-2-1 architecture; 3 input layers, with 2 hidden layers and an output layer. **Figure 10** shows the architecture of the network.

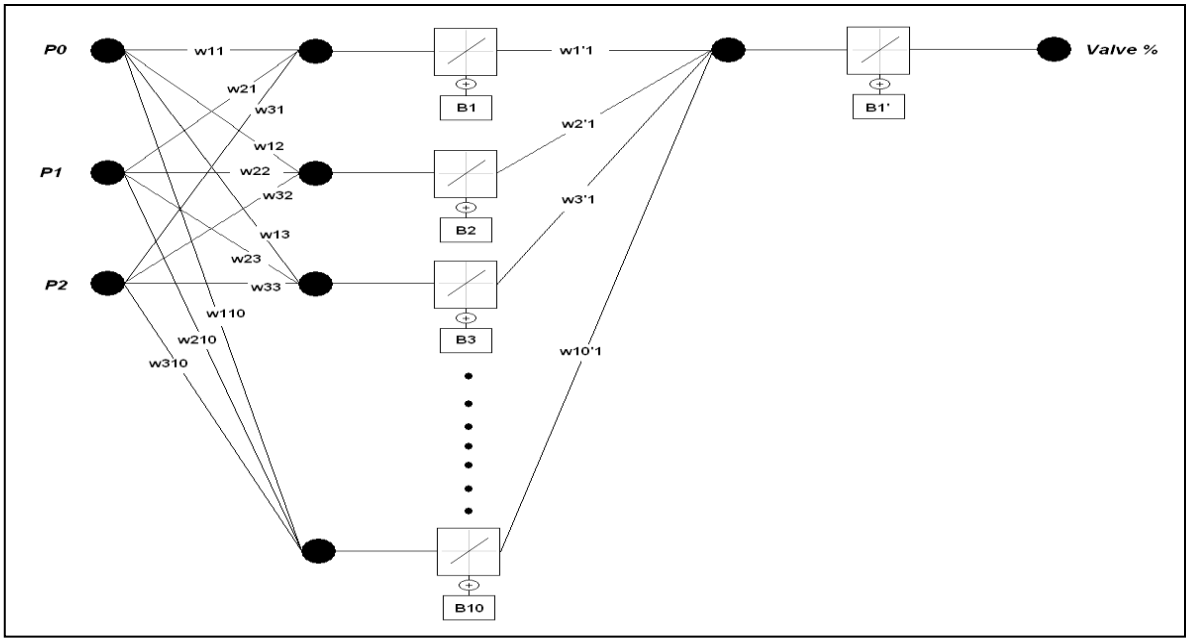

Figure 10 : Neural Network Architecture

The process started with data training to see relationship between the input and output of the system representing the future plant activity. The numbers of training samples used were 1100 data which were obtained from the previous research using CFD analysis. Besides that, number of delayed input and delayed output were determined based on the order of the transfer function.

The process continued by implementing the plant model training as in **Figure 11** and **Table 2**. In order to determine the best training algorithms in terms of fastest learning rate and least error achieved, the plant was trained using 11 different algorithms. The Epochs number was set to 200 with Mean Squared Error of 0.001. This means that the system will try to achieve the goal Mean Squared Error of 0.001 in maximum 200 iterations.

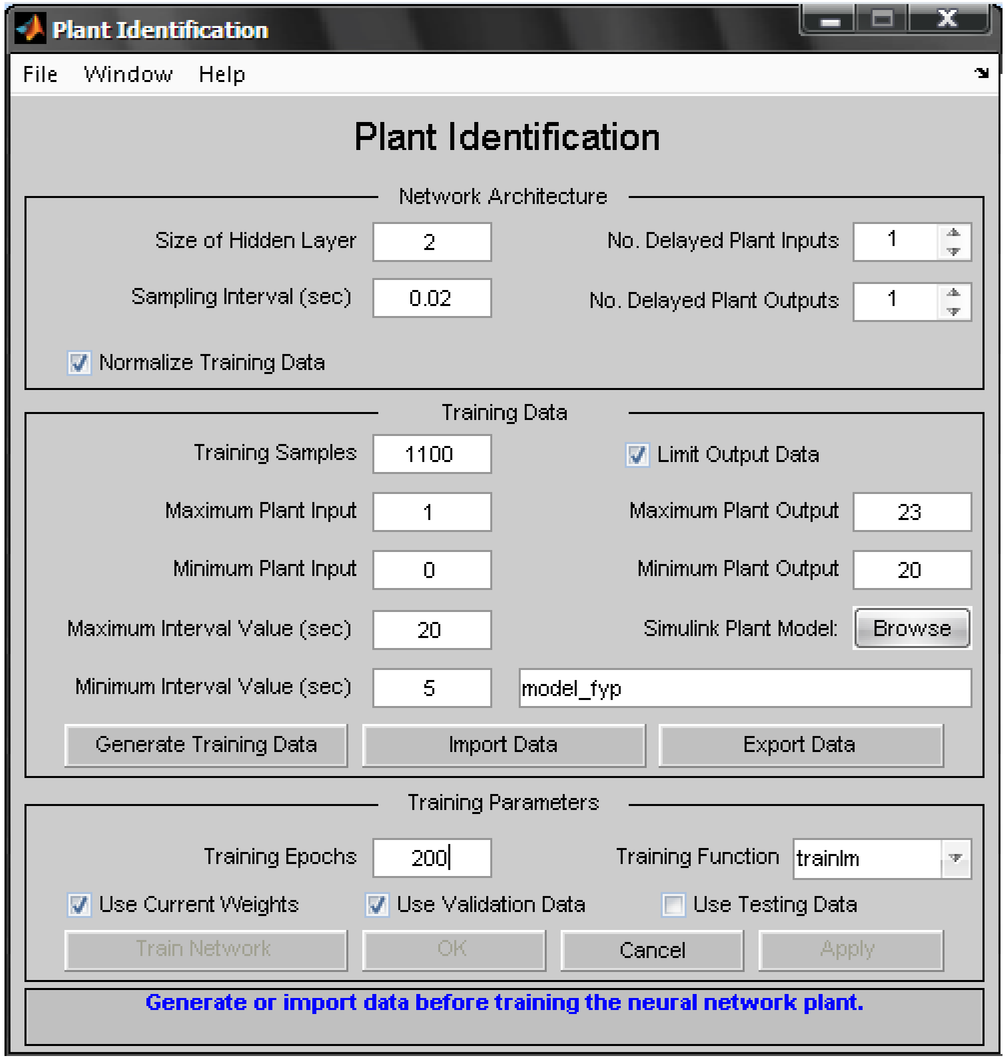

Figure 11 : Plant Identification Diagram

Table 2 : Functions in Plant identification

Parameters	Description	Value
Size of Hidden Layer	The number of neurons in the first layer of the plant model network.	*2*
Sampling Interval (sec)	Interval at which the program collects data from Simulink model.	*0.08*
No.Delayed Plant Inputs	The size of the delay lines coming into the plant model	*2*
No.Delayed Plant	The size of the delay lines coming into	*2*

Outputs	the controller; increases with the order of the plant.	
Training Samples	Number of data points generated for training, validation and test sets.	*1100*
Maximum / Minimum Plant Input	Range on the input data to be used in training.	
Maximum / Minimum Plant Output	Range on the output data to be used in training.	
Simulink Plant Model	Model to generate training data.	*model_fyp*
Generate Training Data	Button to start the training data generation.	-
Training Epochs	Number of iterations of plant training to be performed.	*200*
Training Function	Selection of training function to train the plant model.	*Trainlm (Levenberg-Marquardt)*
Train Network	Button to start the plant model training.	-

The configurations for the controller were done as in **Figure 12** by determining the following parameters:

- The control horizon N_u , determine the instant time on when the output of the controller should be kept at a constant value.
- The cost function is often used with the weight factor $\rho = 0$. However, by using higher ρ, the control signal is smoother as it is used to penalize excessive control effort.
- The cost horizon,N_2, which is the maximum prediction horizon is just set to be higher than Nu.

The following values were chosen for the tuning parameters of the predictive control algorithm; $N_2 = 7$, $N_u = 2$, $\rho = 0.05$. Final simulation was done on Simulink plant model to obtain the plant output which was compared to the reference signal.

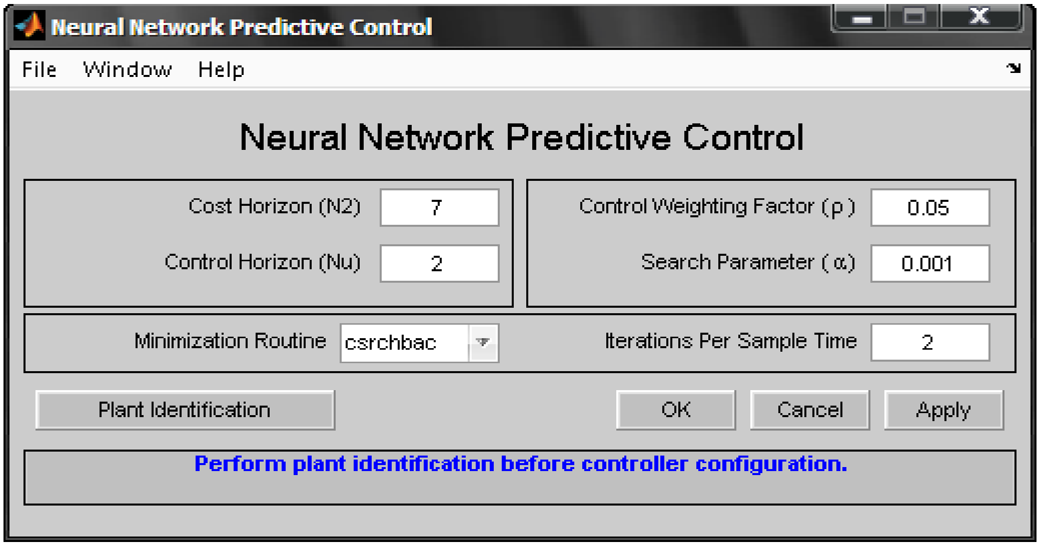

Figure 12: NN Predictive Controller Configuration Diagram

3.6 Tools and Equipment Required

3.6.1 System Identification and Graphical User Interface (GUI) in MATLAB R2007a

This software used to perform estimation and validation on the system based on input-output data.

3.6.2 MATLAB R2007a Simulink

This software used to do simulation for the best model system configured from the System Identification and will be used for designing the controller as well as during the step to implement it on the system.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 System Modeling

System Identification Toolbox™ software is chosen as it can construct mathematical models of dynamic systems from measured input-output data. This data-driven approach helps to describe systems that are not easily modeled from first principles or specifications. It also helps to simplify detailed first-principle models, such as finite-element models of structures and flight dynamics models, by fitting simpler models to their simulated responses [13].

4.1.1 Transfer Function

Based on the System Identification Tools, a First Order-With-Dead Time model was obtained using Process Model technique with model fits up to 76.32% with the original data**.** The value of each parameter is automatically generated from simulation with 20 iterations. The transfer function for the system is as below:

$$\frac{Gp\,(s)=0.014175\,e^{-0.076749\,s}}{1+1.784s} \qquad \text{(Eq.5)}$$

4.1.2 Input-Output Data

Figure 13 shows the graph for the raw data which y1 is the graph for shockwave position (meter) and u1 is the graph for the valve opening (%).

From the graphs, it was observed that the shockwave position is proportional to valve opening. The control zone for shockwave position is between 0.95m to 1m from the sonic throat. In order for the dehydration process to be possible, the optimum valve opening is within 66.8% and 70%.

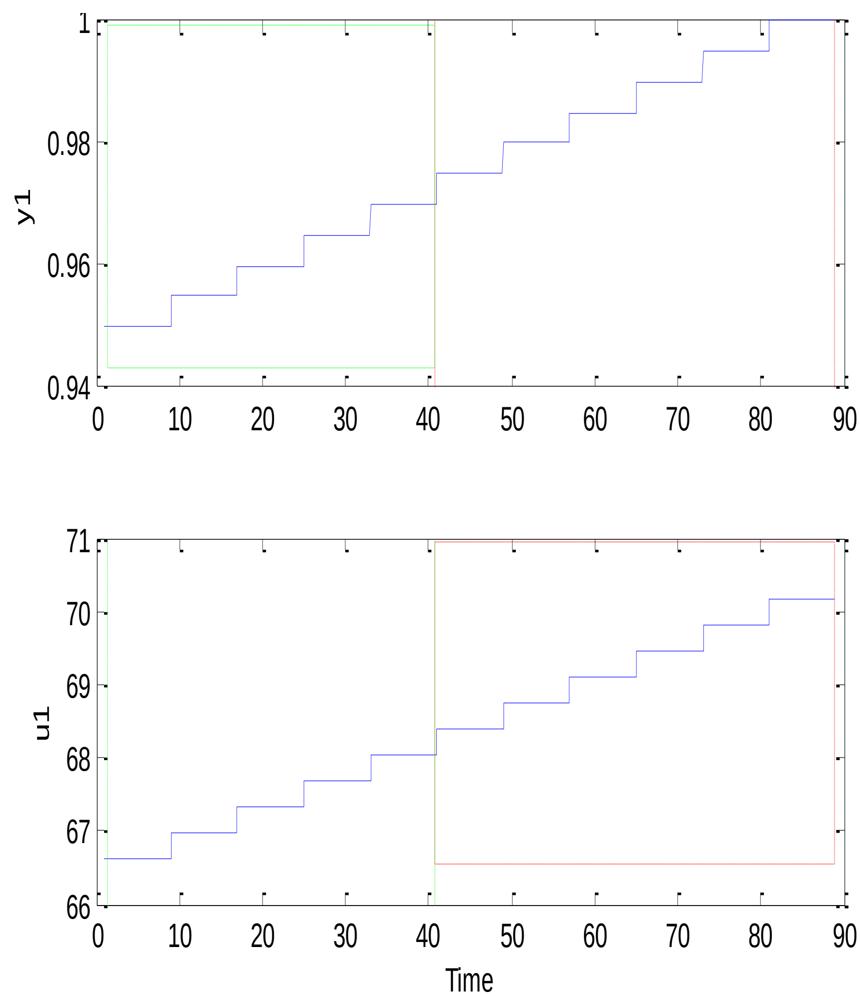

Figure 13: Input-Output Data

It was observed that at certain periods, the valve opening is constant most probably due to the feed gas pressures in the supersonic separator nozzle that decreased in velocity from the supersonic to subsonic. The feed gas pressures did not show vigorous effect due to subsonic profile. As a result, valve opening percentage shows constant manipulation as well as shockwave position.

4.2 PID Controller Tuning

Since one of the objectives of this research is comparing NN Predictive Controller with the existing PID algorithm controller, thus the following procedures are the tuning process for the model obtained previously. The simulation was done using Simulink as shown in **Figure 14**.

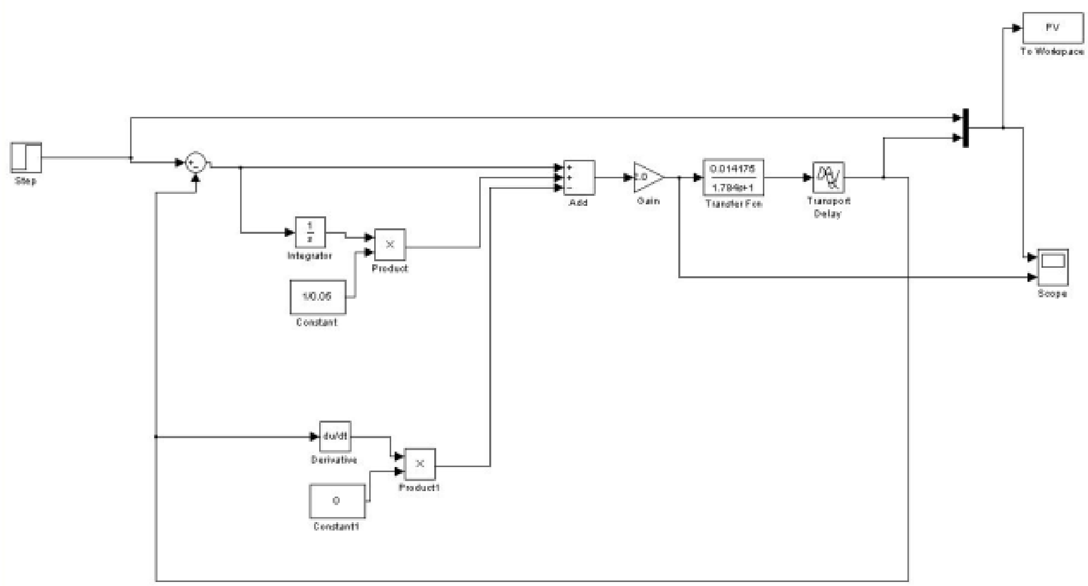

Figure 14 : PID Controller Block

It was observed in **Figure 15** that although the shockwave achieved optimum position at 1m by 70% of valve opening but it takes a long time with T_s = 38.5s. The Controlled Variable (CV) response was very slow with rise time, T_r = 27s. The Manipulated Variable (MV) response in **Figure 16** shows that there was merely no overshoot of valve changes in order to compensate the situation.

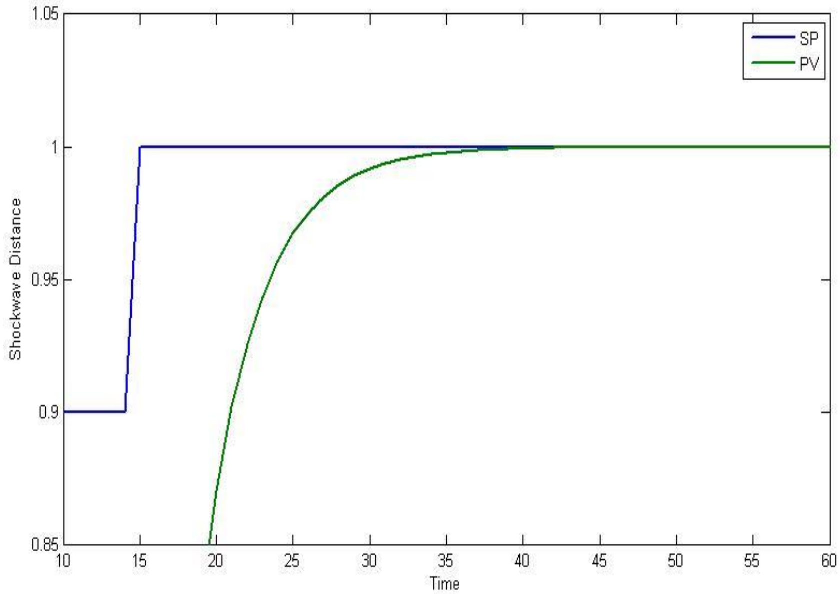

Figure 15 : CV Response Before Tuning

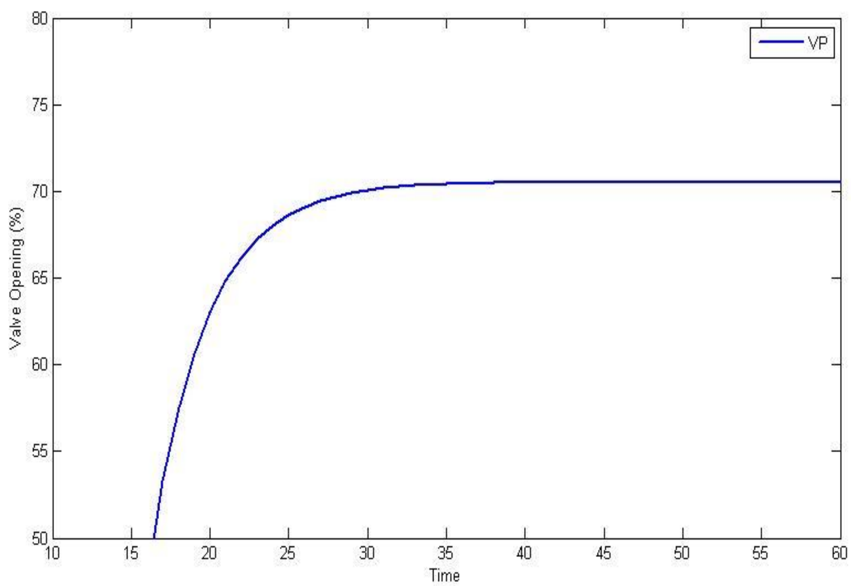

Figure 16 : MV Response Before Tuning

For this system, it was observed that the most suitable controller mode is the PI mode. The response of the system is already fast thus it does not need a derivative mode as it will create aggressive response in the system. The initial $K_c = 1.44, T_i = 0.5s$ and $T_d = 0$.

In order to improve the response, fine tuning has been applied for the related PID mode. One of the most obvious effects of the proportional mode can be seen at the initial change of MV. Thus, for this system K_c has been increased to $K_c = 2.0$ and response become well as in **Figure 18**.

Integral mode enables the controller to achieve zero offset. Integral time also affects the amount of time zero offset achieved. After fine tuning, the best value is $T_i = 0.05s$. Reducing integral time produced a bigger MV signal and can shorten settling time as in **Figure 17**. However, too small integral time can also cause the CV to oscillate and approaches instability.

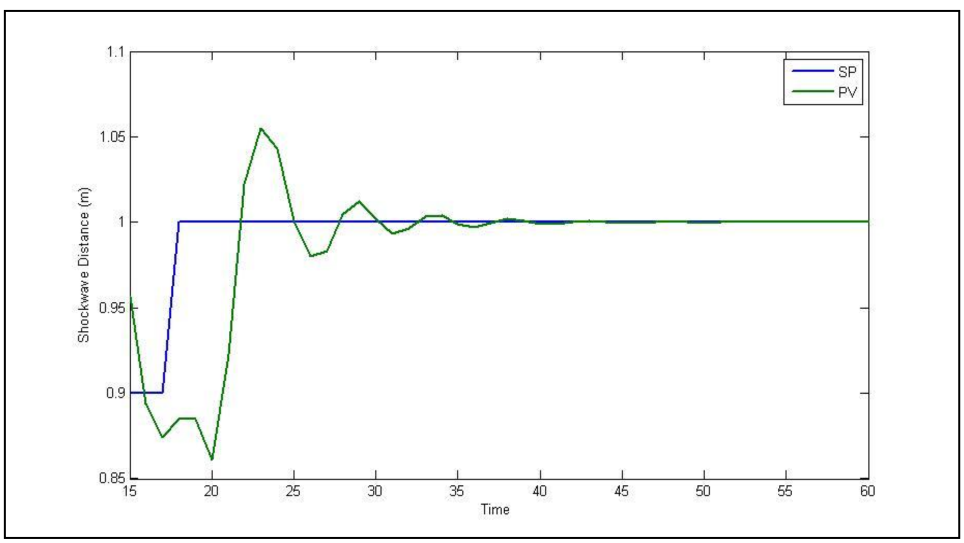

Figure 17 : CV Response After Tuning

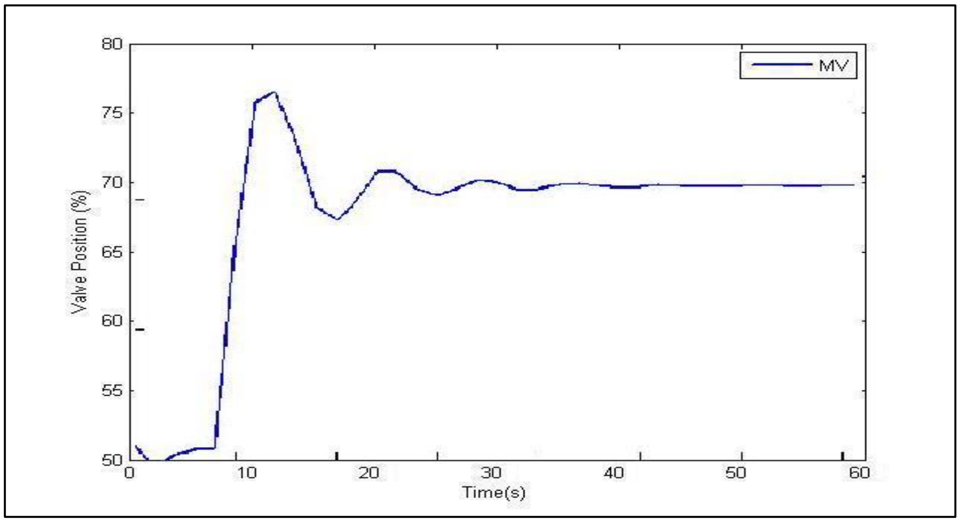

Figure 18 : MV Response After Tuning

The initial change of valve is quite high shown that the valve tends to act vigorously due to the feed gas pressure change with overshoot of 30%. When the shockwave is at the optimum position which is 1m, valve started to reduce the opening to 70% in order to reduce the flow of feed gas. Besides, the process took less time with T_s = 37s and faster with rise time, T_r = 22s to reach optimum shockwave position to make sure gas attained full dehydration. However the response contained ripples with decay ratio of 3.3 and this will affect the stability if in dynamic condition.

4.3 Neural Network Predictive Controller Simulation

The Levenberg-Marquardt (trainlm) algorithm has been identified to give the least error and fastest learning rate. The system was able to achieve the goal of Mean Squared Error with value 0.000188 within 2 iterations. **Figure 19** and **Figure 20** shows the response based on the Neural Network Predictive Controller.

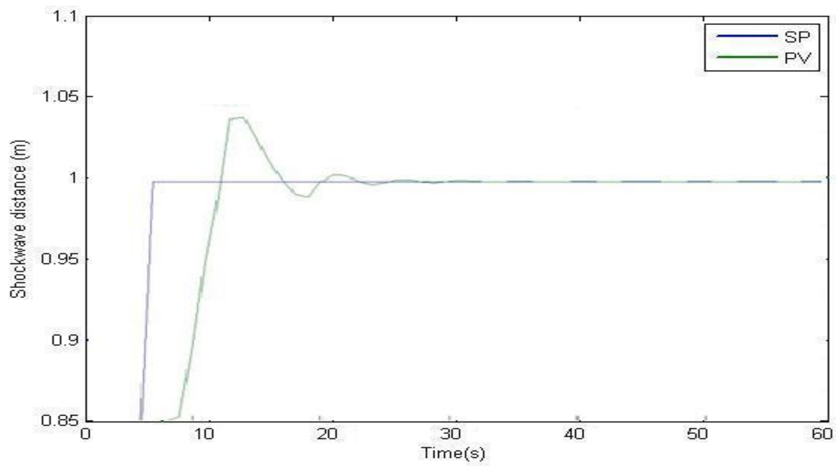

Figure 19 : CV Response in Simulink Plant Model

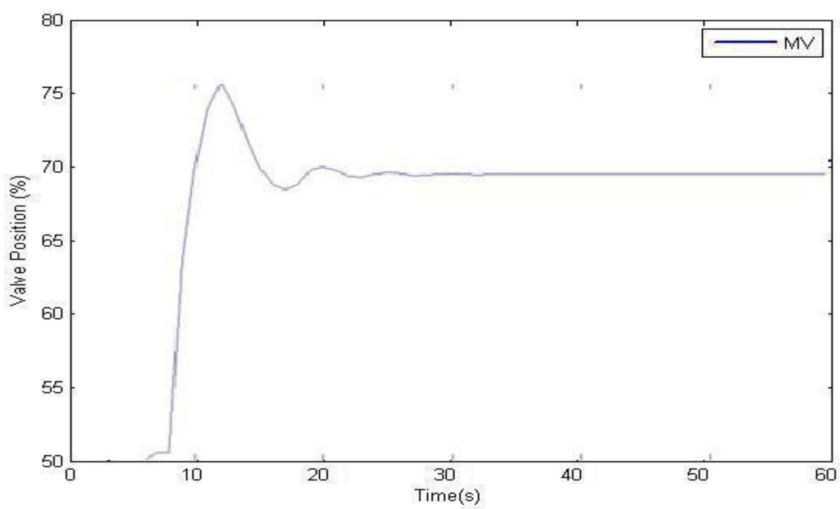

Figure 20 : MV Response in Simulink Plant Model

The initial change of valve is quite high shown that the valve tends to act vigorously due to the feed gas pressure change with overshoot of 23% which is slightly lower than PID algorithm response. When the shockwave is at the optimum position which is 1m, valve started to reduce the opening to 70% in order to reduce the flow of feed gas. The process took less time with T_s = 29s and faster with rise time, T_r = 12s to reach optimum shockwave position. Compared to PID response, this controller shows a better response and contained less ripple with decay ratio of 2.5. The response with less fluctuation will increase the stability. **Table 3** shows the comparisons of performances between PID controller and Neural Network Predictive controller with the raw data.

Table 3 : Comparisons for Controller Performances

Condition / Parameter	Raw Data	PID Controller	Neural Network Predictive Controller
Rise Time, T_r (s)	27	22	12
Settling Time, T_s (s)	38.5	37	29
Overshoot, OS (%)	-	30	23
Decay Ratio	-	3.3	2.5

From this result, it has been proven that a Neural Network Controller is able to handle the non-linear properties of a high pressure and supersonic velocities besides of increasing the efficiency of the system. The Neural Network Predictive Controller is applying both architectures which are feedforward and feedback. The feedforward system architecture allows for a compensation action to be made at an instance a disturbance is sensed before the process is interrupted. The feedback system gives an advantage on making a corrective action after an interruption is sensed in the process. As a result, the implementation of Neural Network controller is able to keep the system in the desired operating region and maintain the process at maximum efficiency.

In other hand, Neural Network controller also consists of back propagation paradigm which allows the output to be predicted based on the input/output correlations. The output is then predicted based on this correlation and not directly from the input compared to PID algorithm. This means that the proposed Neural Network controller is able to reduce the ripples on the output and therefore increasing its stability which is the main concern in controlling compressible flow.

CHAPTER 5
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

From this research it is concluded that a compressible supersonic flow can be numerically modelled. By using System Identification, the properties of the response are compatible with the manual calculation done in Empirical modeling.

Simulation of the system modeling with PID algorithm proved that PI mode is the most suitable algorithm in order to obtain a good response. However, although in a static condition the PID algorithm shows that the pressure relation is linear, somehow the fluctuations in a dynamic condition will cause the system to swing out of stability and its linearity.

From the simulation, concluded that Neural Network Predictive Controller is able to handle the non-linear properties and able to keep the system in the desired operating region. Neural Network controller is able to reduce the ripples on the output and therefore increasing its stability compared to existing PID algorithm controller.

As far as this research is concern, the objectives have been met. However, there are still lots of improvements that can be made. These are further discussed in the Recommendations part.

5.2 Recommendation

Based on the current results, the accuracy of the simulation can be optimized by several improvements in parameters configuration and simulation analysis.

The system modeling can be improved with better response and higher order by applying other model alternatives in the System Identification. By examining other types of models, it will validate into which regressors have the strongest effect on the model output of nonlinear model.

As for Neural Network Predictive Controller, further research can be done on how to determine the cost horizon, N_u, and control horizon, N_2. The result may imply a better optimum control input to be applied in the nonlinear plant.

It is recommended to do the whole simulation on a real plant. Thus, the research will be more efficient and the results will be more reliable which aimed to propose Neural Network Predictive Controller to handle nonlinear process of gas dehydration for a supersonic separator.

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APPENDICES

APPENDIX I

LOADING EXCEL FILES INTO .*M* – FORMAT

```
clc
clear all

%Define input name
InputName={'P01,PT1,PT2'}
OutputName={'VP'}
NumberofData='[1:1100]'

data1='Upstream_Profile'
data2='Upstream_Downstream_Relation'

P01=xlsread('input1.xls','sheet1');
PT1=xlsread('input2.xls','sheet1');
PT2=xlsread('input3.xls','sheet1');
Y1=xlsread('output.xls','sheet1');
VP=xlsread('output2.xls','sheet1');
```