ANALYSIS OF BOILER TUBE LEAKAGE BY USING ARTIFICIAL NEURAL NETWORK

by

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CERTIFICATION OF APPROVAL

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

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(WAN NORIZAN BT. WAN AMAT)

ABSTRACT

Artificial neural network (ANN) models, developed by training the network with data from an existing plant, are very useful especially for large systems such as Thermal Power Plant. The project is focusing on the ANN modeling development and to examine the relative importance of modeling and processing variables in investigating the unit trip due to steam boiler tube leakage.

The modeling and results obtained will be used to overcome the effect of the boiler tube leakage which influenced the boiler to shutdown if the tube leakage continuously producing the mixture of steam and water to escape from the risers into the furnace. The Artificial Intelligent-ANN has been chosen as the system to evaluate the behavior of the boiler because it has the ability to forecast the trips.

Hence, the objective of this study has been developed to design an ANN to detect and diagnosis the boiler tube leakage and to simulate the ANN using real data obtained from Thermal Power Plant. The feed-forward with back-propagation, (BP) ANN model will be trained with the real data obtained from the plant.

Training and validation of ANN models, using real data from an existing plant, are very useful to minimize or avoid the trip occurrence in the plants. The study will focus on investigating the unit trip due to tube leakage of risers in the boiler furnace and developing the ANN model to forecast the trip.

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CHAPTER 1

INTRODUCTION

A steam boiler is a covered container that furnishes a method for combustion heat to be transferred into water until the water becomes steam. The steam is then utilized for further energy conversion processes. The water wall tubes, superheater, evaporator, re-heater and economizer are the main parts of the steam boiler. These parts in the boiler are functioning in capturing the thermal energy in the combustion gases to evaporate the water into steam.

For the selected thermal power plant, large number of operational data is captured continuously by the on-line plant's simulating system for its proper operation. These are usually stored as database only. Using these data, ANN models can be modeled for the simulation of the plant operation as we have done in the present study. ANN models are useful as they can be trained occasionally with latest data and these models are easy to use, fast in response and suitable for off-line and on-line applications.

In the present work, the ANN model was trained and validated using real site data to investigate the tube leakage in the evaporators. The related variables were classified and the most influencing on were considered in the ANN model. The variable "Low Temperature Superheater Right Wall Outlet Before Supreheater Dryer" (V20) is assumed to be the main contributor to the shutdown.

1.1 Background of Thermal Power Plant

The primary function of a steam boiler is to produce steam at a given pressure and temperature. In order to accomplish this function, the boiler serves as a furnace where air is mixed with fuel in a controlled combustion process to release large quantities of heat. The pressure-tight construction of a boiler provides a means to absorb the heat from the combustion and transfer this heat to raise water to a temperature such that the steam produced is of sufficient temperature and quality (moisture content) for steam loads. The main components and systems of the thermal power plant boiler are shown below.

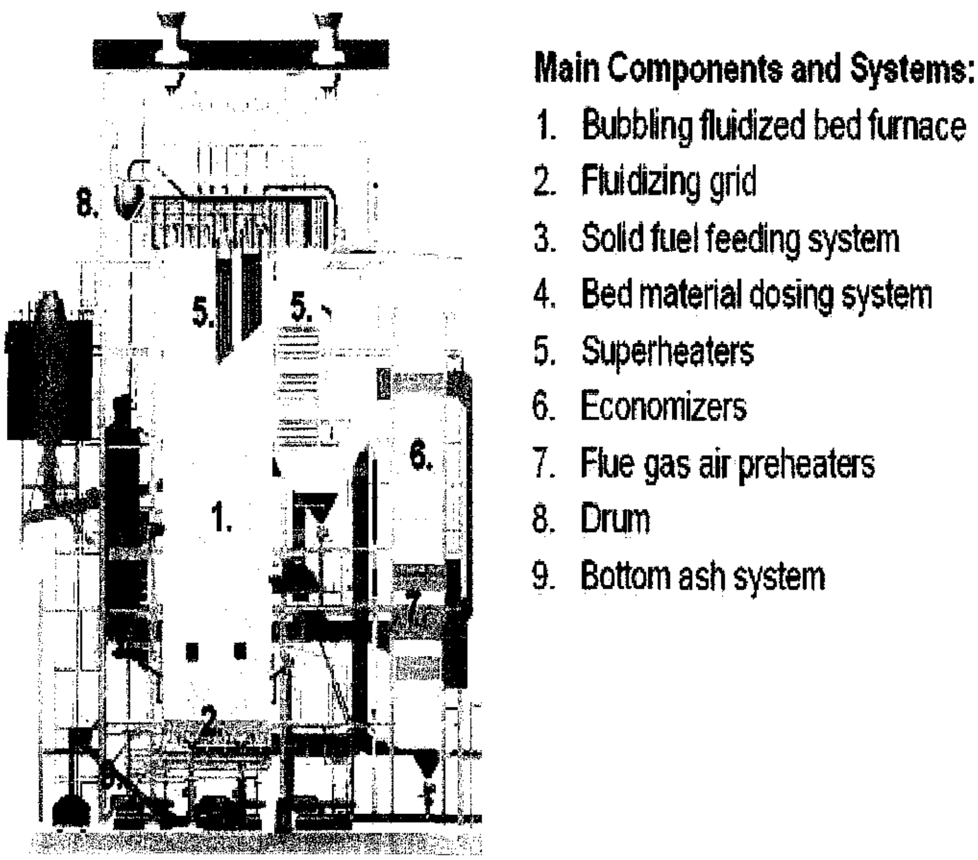


Figure 1.1 Schematic Diagram of Thermal Power Plant Boiler [3]

The boiler has an enclosed space where the fuel combustion takes place, usually referred to as the furnace or combustion chamber. Air is supplied to combine with the fuel resulting in combustion. The heat of combustion is absorbed by the water in the risers or circulating tubes. The density difference between hot and cold water is the driving force to circulate the water back to the steam drum. Eventually the water will absorb sufficient heat to produce steam.

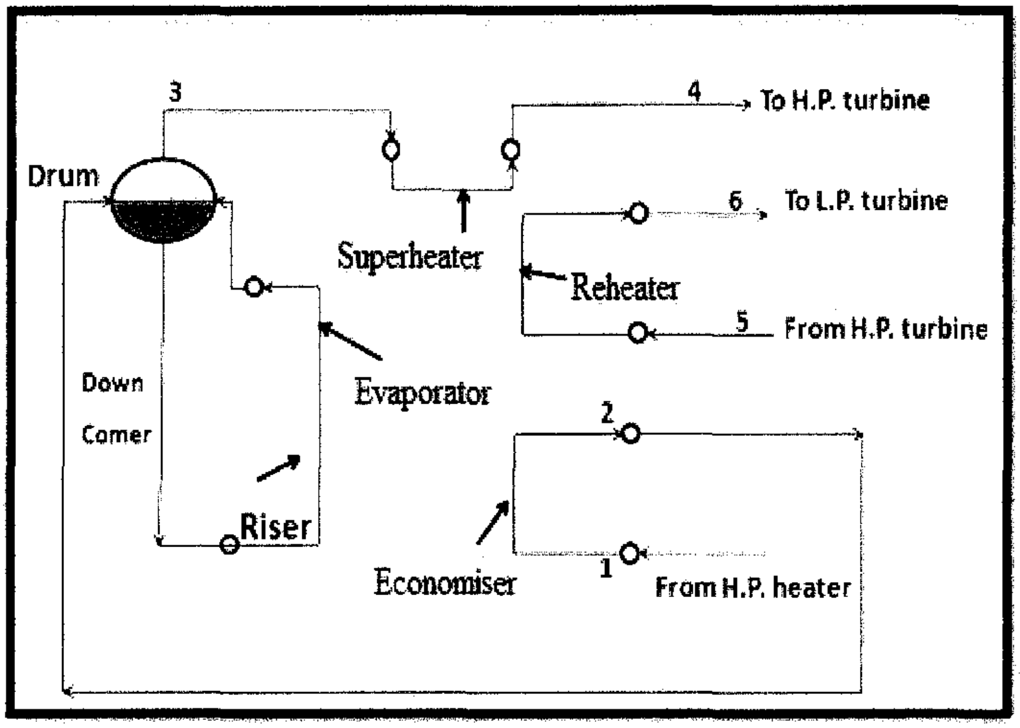


Figure 1.2 Typical Boilers [4]

In the boiler, feedwater is heated in three kinds of heat exchanger (economizer, evaporator and superheater). Feedwater from high pressure (h.p) heater enters the economizer where it is heated by outgoing flue gasses then it is fed into the drum. The water enters the drum as saturated water and the saturated water falls through the downcomer into the bottom header and moves up the riser then boiled back to the drum. The saturated water that passes through the downcomer and riser is boiled in the evaporator to become saturated steam before entering the drum once again. Saturated steam goes to the superheaters for being heated to desire temperature before enters the turbine.

1.2 Background of Artificial Neural Network

An artificial intelligence (AI) system is a term that in its broadest sense would indicate the ability of a machine or artifact to perform the same kinds of functions that characterize human thought. AI consists of five major branches, i.e. expert systems, artificial neural networks (ANNs), genetic algorithms (GA), fuzzy logic and various hybrid systems, which are combinations of two or more of the branches mentioned previously.

ANNs are massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects: the knowledge is required by the network through a learning process, and inter-neuron connection strengths, known as synaptic weights, are used to store knowledge.

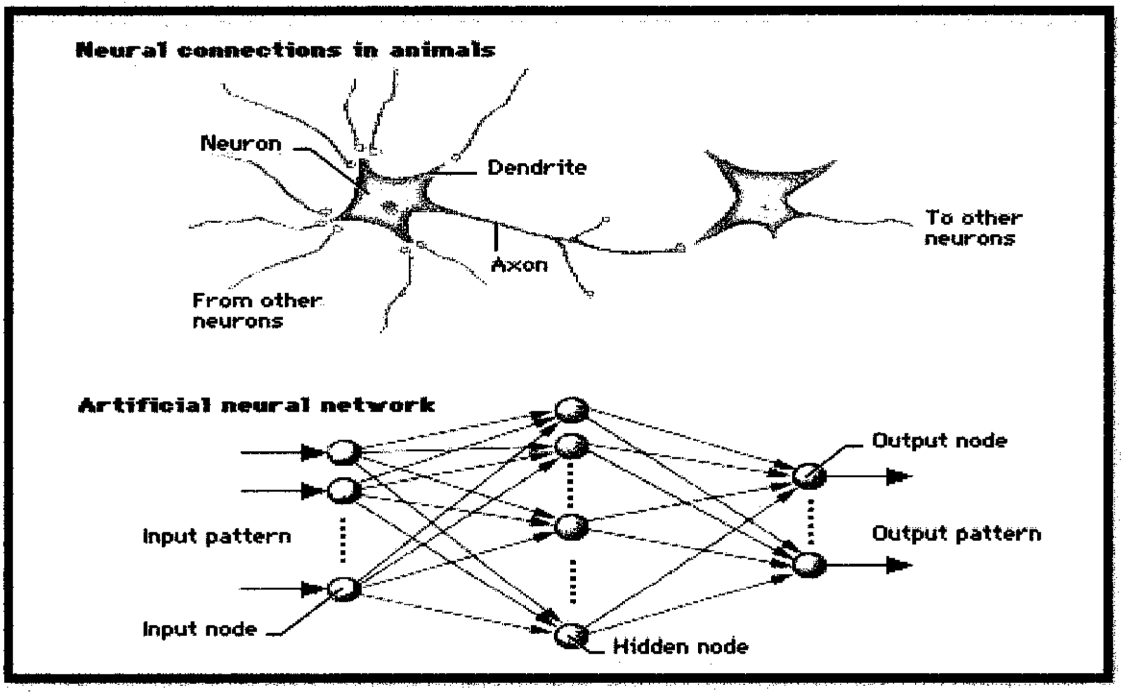


Figure 1.3 A Simplified model of an artificial neuron [15]

ANNs mimic somewhat the learning process of a human brain where they operate like a ``black box" model, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data, similar to the way a non-linear regression might perform. [6]

The multilayer feed-forward neural network usually consists of an input layer, some hidden layers and an output layer and each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights.

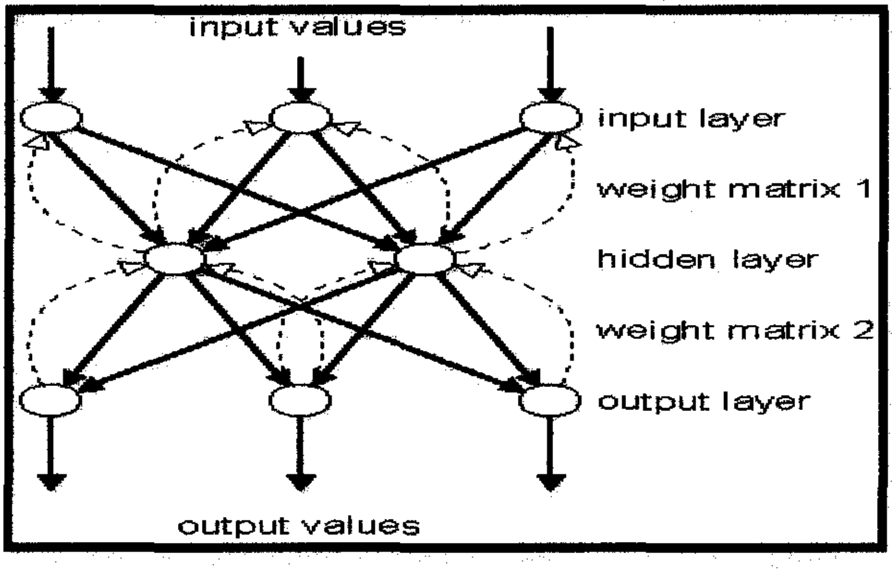


Figure 1.4 The Multilayer Feedforward NN Model [10]

Knowledge is usually stored as a set of connection weights. Training is the process of modifying the connection weights in some orderly fashion using a suitable learning method. The network uses a learning mode, in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. The weights after training contain meaningful information whereas before training they are random and have no meaning. The node receives weighted activation of other nodes through its incoming connections. The training algorithms cannot undergo any training without any activation functions. The activation function is to calculate the weightage of each node introduced into the hidden layer. There are three types of activation functions used; linear transfer function (purelin), log-sigmoid and tan-sigmoid activation functions. Combination of these activation functions will produced different value of output.

First, these input nodes that enters the hidden layers are added up then passed through an activation function; the outcome is the activation of the node. For each of the outgoing connections, this activation value is multiplied with the specific weight and transferred to the next node. When each pattern is read, the network uses the input data to produce an output, which is then compared to the training pattern. If there is a difference, the connection weights are altered in such a direction that the error is decreased. After the network has run through all the input patterns, if the error is still greater than the maximum desired tolerance, the ANN runs again through all the input patterns repeatedly until all the errors are within the required tolerance. When the training reaches a satisfactory level, the network holds the weights constant and the trained network. The functions RMSE is to calculate error between actual output and predicted output. The equation of RMSE used is:

$$RMSE = \frac{1}{Q}\sum (t(k) - a\,(k))^2$$

K = number of iterations

Q = total number of iterations (epochs)

t = target output

a = actual output

1.3 Problem Statement

Risers are installed all around the four walls of the furnace act as cooling tubes or a water wall and carry away the heat from the furnace at the same rate at which heat is released in it by burning of fuel. Adequate circulation of water must be provided in the circuit as shown in Figure 1.5. If the circulation is not adequate, then rate at which heat from the furnace is carried away from the risers will be less than the rate of heat transferred to the risers and the difference will be stored in the metal of the riser tubes leading to their overheating and ultimately rupturing when the tube temperature exceeds the melting point of the metal.

Usually the riser tubes have more thermal loading and generate more steam because they are located opposite to the burners. Too much steaming in a riser tube is not preferable. On the heated surface, the bubbles are originated and the formation of the bubbles will be higher if there is a high rate of heat transfer to the riser. The bubbles may coalesce and first form an unstable vapor film which continually collapses and reforms.

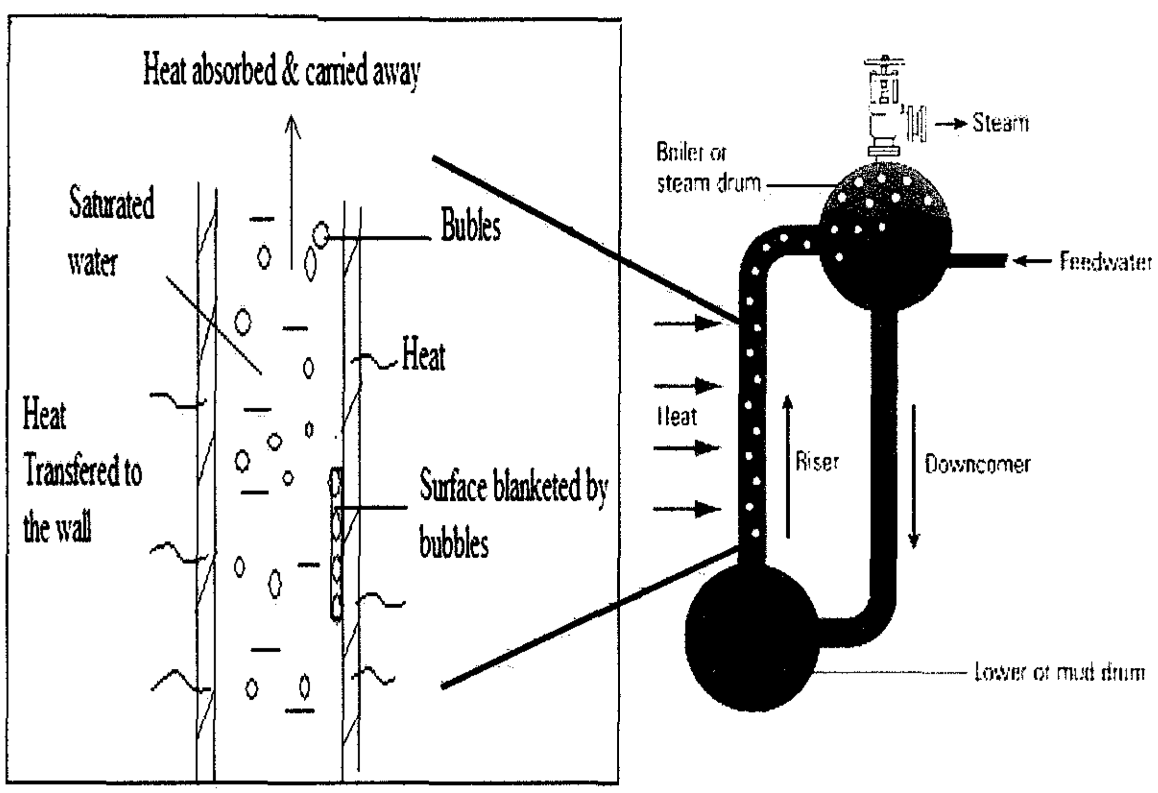


Figure 1.5 Nucleate and Film Boiling in a Riser Tube [2]

Since the vapor film as shown in the figure 1.5 above has much lower thermal conductivity than a liquid film, it will offer a large thermal resistance, almost blanketing the surface where it forms. The difference between the heat absorbed and heat transferred to the wall will be stored in the metal of the tube with the increase in its internal energy. Hence, consequently the temperature of the metal may exceed the melting point and the tube may rupture allowing tube leakage [2].

Leakage of risers will produce the mixture of steam and water to escape out from the risers into the furnace. The mixture of steam and water will decrease the heat of the furnace and slowly reduce the temperature of the superheater which situated at the upper part of the furnace.

1.4 Objectives and Scope Of Study

Objectives have been structured and strongly needed to be achieved at the end of this project in order to analyze the importance of the variables of the steam boiler for prevention of the unit trip.

i. To study the behavior of the boiler operation variables of the steam boiler.

ii. To design an ANN model for detection and diagnoses of the boiler tube leakage trip.

The scope of this research is to develop ANN modeling using different NN Topologies and locate the best ANN topology combination for fault diagnosis and detection (FDD).

CHAPTER 2

LITERATURE REVIEW

M. Fast [2009] has presented a paper on *Application Of Artificial Neural Networks To The Condition Monitoring And Diagnosis Of A Combined Heat And Power (CHP) Plant*. In his paper stated that the objective of his study has been to create an online system for conditioning monitoring and diagnosis of a combined heat and power plant in Sweden [13]. The artificial neural network (ANN) models were integrated on a power generation information manager server in the computer system of the combined heat and power plant. The CHP components were simulated with ANN and the models were integrated in a power generation information manager (PGIM) server in the computer system of the CHP plant.

The plant system was divided into its basic components, and each component was modeled separately. Data from the plant was delivered as 5-min averages, covering three months of operation. Before using any data for training, the data had to be filtered and outliers (removed). Also all transient operations were removed since 5-min average data only permitted modeling of the steady state operation. The selection of input and output parameters, for each individual model, was based on the availability of reliable plant data as well as true needs. All ANN models were subjected to a sensitivity analysis in order to assess which input parameters were of significance for each model.

The performance of a gas turbine is determined by the ambient conditions and using these conditions as input parameters to the ANN model is a natural course of action. The two discrete load cases were represented by two 'switches' ('1' and '0'), enabling the NN to differentiate between two modes of operation based on load. In boiler model, only two inputs (temperature and pressure of feedwater) were required for the ANN boiler model in order to obtain predictions of the steam properties and the mass flow rate of pellets. With proper training, data and parameter selection, it is also feasible to achieve very high prediction accuracies. The condition of a plant could be monitored while simultaneously economically evaluating deviations.

The parameters of HRSG, district heat and input parameters of the boiler, e.g. fuel and air flow rates and air temperature is included to see the effects on the power output. Other parameters like drain pressure and the Curtis pressure have been used as input parameters in order to increase the accuracy of the ANN model. The ANN models are found to have very good prediction accuracy. By predicting the power output with good accuracy, online monitoring system for the plant and the assessment of degradation of the performance of the plant can be implemented.

In the paper of *Comparison of Fuzzy logic and Neural Network in life prediction of boiler tubes* written by *A. Majidian* [2009], wall thickness of reheater tubes of boiler of Neka power plant in north of Iran are measured during maintenance shutdown period [1]. This study has investigated the thickness dependency versus time and it shows that about 40% of tube failures occur in furnace water wall tubing and several primary mechanisms have been found responsible for the boiler tube failure experienced in power plant boilers. Secondary failure mechanisms (adjacent tube washing / impact) also can produce a tube failure and always a concern after an initial failure.

By implementing ANN, two cases were considered. First, the data of all leading tubes of all bundles were used as input and next, 10 selected tubes were chosen. In order to get the best approximation for wall reduction, multi-layer feed forward Neural Network (ANN) is used. Typically, the more the neurons in hidden layer, the more powerful the network. The number of neurons in the hidden layer is varied to give the network enough power to solve the problem.

Since the objective of this study is to find the minimum remaining life of a set of tubes in the boiler, the worst tube is sought or in other words, seeking for the tube that has the lowest thickness or a redundant wall thickness with a membership value of one and is prone to highest loss of wall thickness or a wall thickness reduction rate with a membership value of one as well. Using 'tansig' as activation function causes the network to approach the solution faster than when using 'logsig'.

From the results, ANN model with one neuron in hidden layer predicts 70% and 31% longer life compared with ANN model with three neurons in hidden layer hence, the number of neurons affect the results of maximum wall reduction rate. The results indicate that wall thickness reduction rate accelerates with time. The choice of activation function may be significant influence on the results of network. Increasing the number of neurons in hidden layer will decrease the number of calculation steps with subsequent decrease in sum-squared error.

For prevention of utility destruction in power plant, the early boiler tube leak detection is highly enviable. In the study of *Approach to Early Boiler Tube Leak Detection with Artificial Neural Networks* by *A. Jankowska* [2007], the ANN models of flue gas humidity for steam leak detection are presented. The author mentioned that, the plant shutdown, breakdown and catastrophes can be avoided by implanting early detection of faults.

There are several methods of steam leak detection. Hence, the method of steam leak detection can be specified as by implementing acoustic monitoring devices, steam and water balance testing method, monitor the humidity of flue gas whereby the humidity can be caused by water added to combustion chamber, changing fuel hydrogen or steam leaks.

The advantages of using artificial intelligence methods approach to steam leak detection can be named as new devices or signals besides DCS are not necessary, expected earlier leak detection because of using many measured signals and no apparent interdependencies, expected solution portability between like plants [12]. Three structures of ANN models of flue gas humidity were built which are linear nets, radial basis function and feed forward multilayer perceptron.

The models were trained with data compounded from long period of time and next decimated. The learning, testing and validation subsets were distinguished and reconstruction, validation of missing and fault values of measured data is necessary stage in off-line and special in on-line mode of models application.

Hence, due to averaging and generalization properties of ANN external process disturbance were sufficient well presented in model. The tested ANN model gave promising results in early detection of tube boiler faults, but very limited number of faults cases was in disposal [12].

Luis M. Romeo [2006] had presented a research on *Neural Network For Evaluating Boiler Behavior* and the objective of the research is to present the methodology of NN design and application for a biomass boiler monitoring and point out the advantages of NN in these situations [8]. This paper proposes the use of an artificial feed-forward neural networks based model in order to evaluate the biomass boiler fouling.

There are 2 techniques that could be used to develop an accurate boiler monitoring; theoretical thermal modelization and neural networks simulation. The first technique requires strong hardware and software to solve non-linear mathematical operation. However, neural networks simulation technique is able to deal with complex calculation, obtaining accurate results without needing of high developed software. The aim of the develop NN is to produce the value of fouling index obtained by the theoretical model used for monitoring and steam output obtained by real data.

Multilayer feed-forward NN is the structure used in the work where the information goes from the input to the output throughout intermediate layers in a unidirectional way. The methodology applied to develop NN could be theoretically divided in four stages: structure or architecture design, training, validation and use. The NN is training with the available inputs and mean square error (MSE) is registered.

The higher the influence of the absent input in the training is, the more increased the MSE value is, and more important the eliminated input variables are to solve the problem. All the results have been validated with real and equation-based monitoring data. Agreement between data and NN results is excellent and also has been pointed out that the NN is a stronger tool for monitoring.

On the other hand, R.J. Patton [1994] had proposed in his paper on *A New Approach For Detecting And Isolating Faults In Nonlinear Dynamic Processes Using Neural Networks*. Two stages involved and demonstrated in a laboratory 3 tanks system. The first is to generate residual signals based in comparison between actual and predicated states and the second stage of fault detection and isolation, a neural network is trained to classify characteristics contained in the residuals [14]. A neural network is used to examine the possible fault or abnormal feature in the system outputs and gives a fault classification signal to declare whether the system is fault or not.

A laboratory 3-tank system is used as a test bed to demonstrate the method presented in the paper. The NN detects a fault using pattern recognition techniques and activates an alarm signal. In the training of NN to classify faults, output node values of 0.1 and 0.9 are used to indicate fault-free and faulty cases. If fault patterns are known to occur for specific faults, this information could be stored in the neural network by choosing the training set of the neural network to co-ordinate with known faults. The results show that the NN-based fault diagnosis scheme can detect faults in nonlinear dynamic system reliably providing sufficient training.

CHAPTER 3

METHODOLOGY

3.1 Research Methodology

Methodology employed in this project starts with data collection from respective thermal power plant. Apart from that, literature review has been performed by study in details each of the papers (journals) collected which are very closely related. This study needs to be done in order to capture the main ideas of the relevancy of the project which will make the objectives clearer and achievable.

3.2 Preliminary Data Processing

i. Data Collection

The data collected consists of the data generated from all three (3) units of boilers in the thermal power plant and those data need to undergo several steps of procedure before used as the input variables to the NN model. Data collected comprising more than thousand variables.

ii. Data Cleaning

During data collection, large amount of data is captured and then need to be visualized sequentially to detect any missing or unclear data. It is crucial to ensure that all data obtained are relevant and sufficient to develop ANN modeling as the rests are interrelated and thus redundant.

iii. Data Filtering and Normalization

The accuracy of the training by a trained ANN can never be better that that of the training data, thus a critical scrutiny of obtained real data is required to identify and remove these erroneous data which is known as outliers. The erroneous data will affect the data normalization because it will produce error to the system. Hence, filtering is essential steps to be done to delete all the erroneous data. After data filtering, the data need to be normalized or stabilized in order to make sure that the ANN model will detect the data. Hence, the data will normalized from the value more than hundreds into the value between 0 and 1. The data are normalized by using the equation shown below.

$$\text{Normalization equation} = \frac{X - Xmin}{Xmax - Xmin}$$

iv. Data Segmentation (Training and Validation)

Training ANN consists of training and validation. Training and validation had been classified into 70% training and 30% validation whereby these percentages are only will be calculated under data before shutdown.

After training and validation the ANN model by using different activation function and training algorithms, the best activation function with certain training algorithms which produced the smallest root mean square error (RMSE) will be selected to undergo the validation part. The validation part is to train the data once again by using different coding and simulation to finally produce the real forecasted data which occur before the real trip or in other words the forecasted data that detects the trip before the real trip.

DATA SEGMENTATION

TRAINING (70 %)	VALIDATION (30%)

1 ⟵⟶ **1829** ⟵⟶ **2614 (min)**

v. NN Modeling (NN Topologies)

There are 9 types of multidimensional minimization backpropagation training algorithms but only 4 types have been selected to be used in the hidden layer to produce different errors of output. In constructing the ANN model, coding had been constructed based on the number of hidden layers used and types of function (training and validation). This part is the most crucial part whereby simulating each coding is time consuming. The ANN will be modeled by using 1 and 2 hidden layers, each with 1 to 10 neurons which will produce several different desired outputs. The network is trained by using only up to 2 hidden layers is because the RMSE value for the hidden layers more than 2 will be constant. For each hidden layers, the networks are trained using only up to 10 neurons because the value of the neurons will be greater than 1 which cause errors to the networks. The coding of the NN is done by using MATLAB and the types of training algorithms and activation functions used are discussed in details as below.

- **Training Algorithms**

The 4 types of training algorithms are tabulated in the Table 1.1. Function of these four training algorithms is for the convergence of the algorithms of models from ten to one hundred times faster than other algorithms in the NN MATLAB Toolbox. These faster algorithms fall into two categories. The first category uses heuristic techniques, which were developed from an analysis of the performance of the standard steepest descent algorithm. The second category of fast algorithms uses standard numerical optimization techniques.

(Trainrp) **Resilient backpropagation.**	Eliminates the harmful effect of having a small slope at the extreme ends of sigmoid transfer function. It is generally much faster than the standard steepest descent algorithms. It also has the nice property that it requires only a modest increase in memory requirements.
(Trainscg) **Scaled conjugate gradient.**	A search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions. This is a well know, highly efficient algorithm that gives good results on a broad spectrum of problems.
(Trainbfg) **BFGS quasi-Newton.**	This algorithm requires more computation in each iteration anf more storage than the conjugate gradient methods, although it generally converges in fewer iterations.
(Trainlm) **Levenberg-Marquardt.**	Provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function. These minimization problems arise especially in least squares curve fitting and nonlinear programming

Table 3.1 Training Algorithms [11]

Trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. Trainlm is often the fastest backpropagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. However, trainrp is a network training function that updates weight and bias values according to the resilient backpropagation algorithm (Rprop). Trainrp can train any network as long as its weight, net input, and transfer functions have derivative functions.

On the other hand, trainscg is a network training function that updates weight and bias values according to the scaled conjugate gradient method. Trainscg can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance with respect to the weight and bias variables. Finally, trainbfg is a network training function that updates weight and bias values according to the BFGS quasi-Newton method. Trainbfg can train any network as long as its weight, net input, and transfer functions have derivative functions.

- **Activation Functions**

There are three types of activation function used in ANN which consists of linear, tan-sigmoid and log sigmoid.

1. Linear Transfer Function

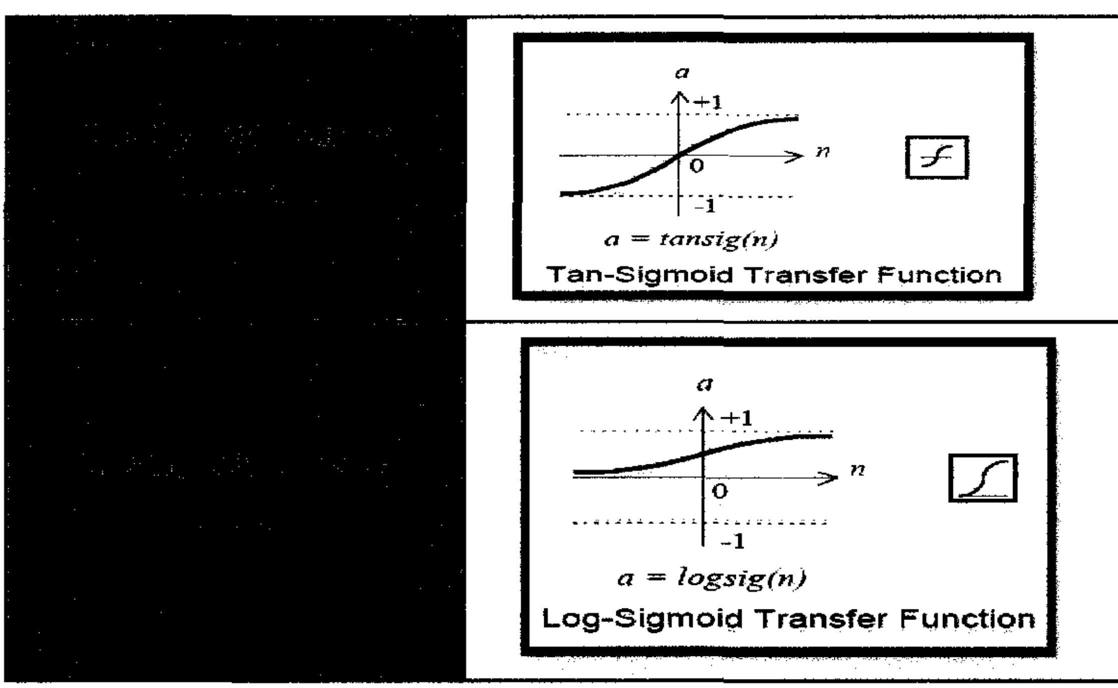
The linear transfer function calculates the neuron's output by simply returning the value passed to it. This neuron can be trained to learn an affine function of its inputs, or to find a linear approximation to a nonlinear function. A linear network cannot be made to perform a nonlinear computation.

2. Log-Sigmoid Transfer Function

This transfer function is commonly used in back-propagation networks, in part because it is differentiable. If the last layer of a multilayer network has sigmoid neurons, then the outputs of the network are limited to a small range. If linear output neurons are used the network outputs can take on any value.

3. Tan-Sigmoid Transfer Function

Multi layer alternatively can use Tan-Sigmoid Transfer function other than Log-Sigmoid.



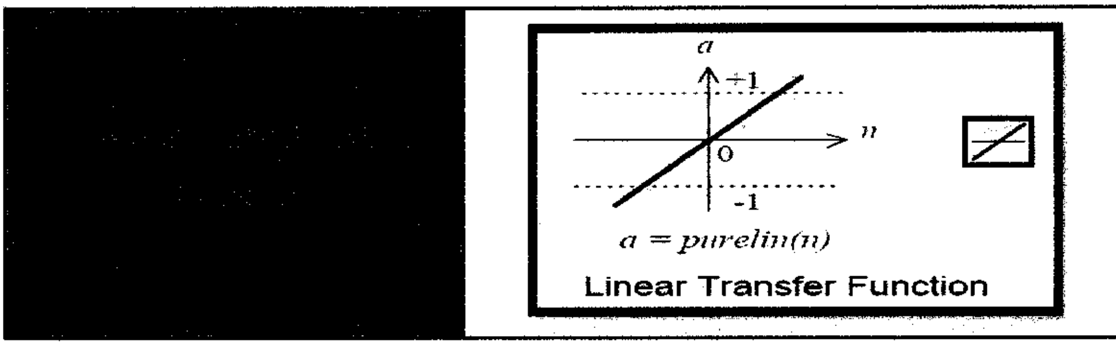


Table 4.2 Types of Activation Functions [11]

The function train carries out such a loop of calculation. In each pass, the function train proceeds through the specified sequence of inputs, calculating the output, error, and network adjustment for each input vector in the sequence as the inputs are presented.

To test the network, the original inputs are presented, and its outputs are calculated with simulation. The simulation will arise in order to measure the performance of each network. The performances of the network are calculated by using root mean square error (RMSE) as shown below in order to find out the weights that minimize error. The smallest the error, the better the output obtained. Then, the desired output obtained from MATLAB will be compared with the actual output and finally will come up with several recommendations and discussions. The RMSE are tabulated accordingly based on the number of neurons and training function and the smallest RMSE are identified based on the data collected.

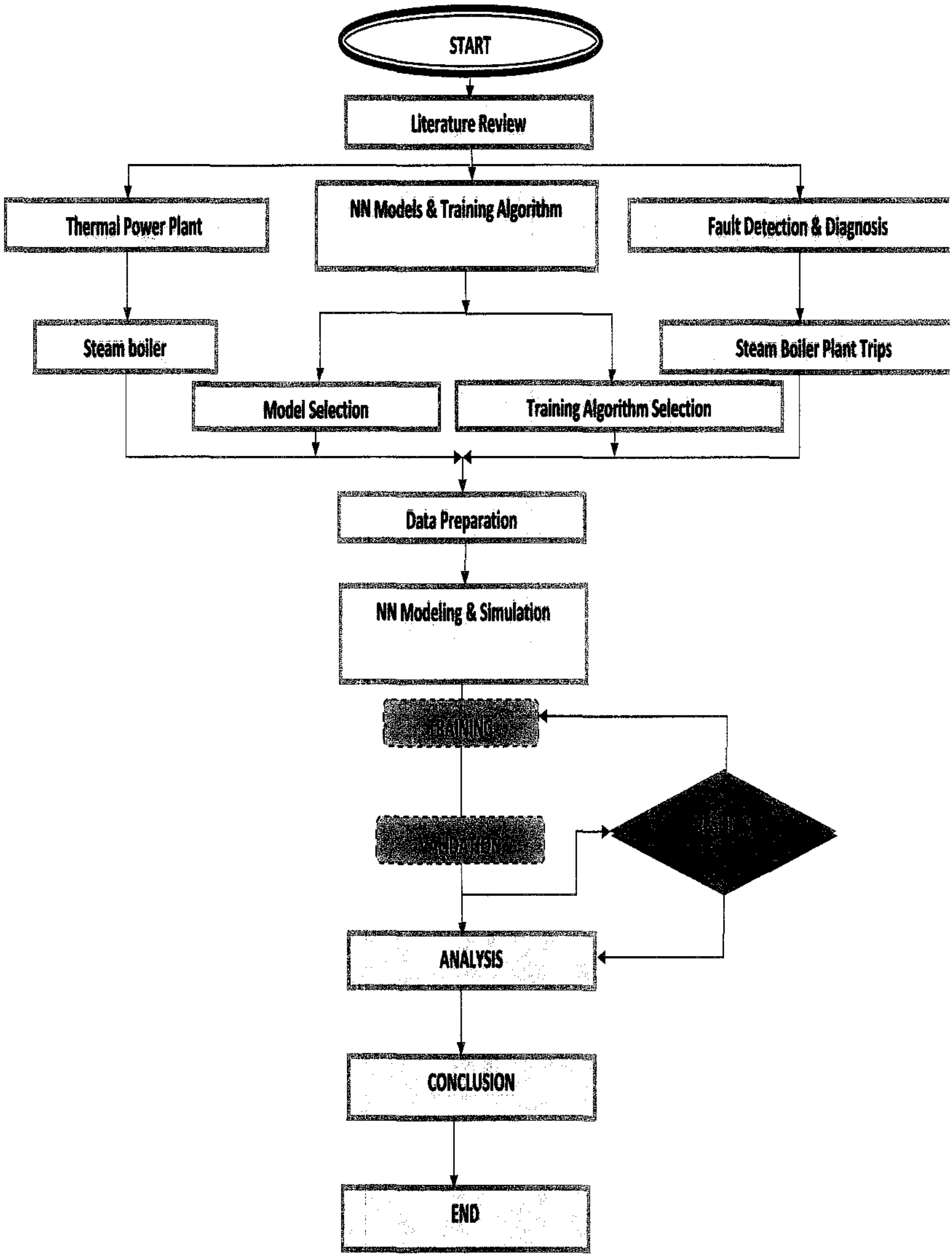
K = number of iterations

Q = total number of iterations (epochs)

t = target output

a = actual output

3.3 Project Activities



3.4 Gantt Chart (FYP I) & Gantt Chart (FYP II)

Refer to Appendix

3.5 Tools Required

FYP I	FYP II
MICROSOFT EXCEL MATLAB	MICROSOFT EXCEL MATLAB (NN ToolBox)

For both FYP 1 and FYP 2, the tools used for simulation of the data are Microsoft Excel and MATLAB.

CHAPTER 4
RESULTS AND DISCUSSION

The objective of data gathering and collection which explained previously is to construct ANN model which can finally forecast the trip before the real trip. The unit selected for this project is boiler unit 1 (sub-critical pressure unit) whereby the unit is shutdown due to the leakage of the boiler tubes. Based on the real data collected from the selected thermal power plant, the unit has been shutdown from 25th April 2008 until 30th April 2008 and it is approximately about 5.17 days according to the plant annual outages.

After undergo the data processing procedure, the data are shortlisted into 32 important variables based on plant operator experience as listed in table 4.1. The variables are shortlisted based on the critical sensors that contributed to the trip of that particular unit of boiler. Among all those 32 variables, there are several variables that had been identified contributed to the trip before the real shutdown. However, this study is focused on the trips which arise before the real shutdown. All those contributions to the trip from each variable are evaluated and classified as "the influenced" (TI) and "the most influenced" (TMI) if the trip occurs slightly a few minutes before the real shutdown.

Based on the fault introduced table below, variable 20 (V20) is classified as TMI because the trip occurs after 2612 minutes of operation whereby the real shutdown occurs after 2615 minutes. The difference between V20 and the real shutdown is less than three (3) minutes. Hence, this variable is very important because it caused immediate trip to the boiler once the sensors detect the fault. This situation is surmountable when implementing ANN model because the model can forecast the trip earlier and the operators of the plant will have sufficient period to overcome the real shutdown.

Table 4.1 Fault Introduced in Trip 1

Var.	Description of the Sensors	Unit	Fault Introduced (Minute Intervals)
V1	Total Combined Steam Flow	T/H	705
V2	Feed Water Flow	T/H	704
V3	Boiler Drum Pressure	Barg	704
V4	Superheater Steam Pressure	Barg	704
V5	Superheater Steam Temperature	Deg C	2471
V6	High Temp. Re-Heater Outlet Temp.	°C	963
V7	High Temp Superheater Exchange Metal Temp.	°C	-
V8	Inlet Temp Superheater Exchange Metal Temp.	°C	2472
V9	High Temp. Superheater Intermediate Header Metal Temp.	°C	2471
V10	Final Superheater Outlet Temp.	°C	-
V11	Superheater Steam Pressure Transmitter	Bar	2471
V12	Feedwater Valve Station	T/H	704
V13	Feedwater Control Valve Positon	%	704
V14	Drum Level Corrected (Ctrl)	Mm	2214
V15	Drum Level Compensated (From Protection)	Mm	704
V16	Feedwater Flow Transmitter	%	-
V17	Boiler Circ Pmp1 Pressure	Bar	2031
V18	Boiler Circ Pump2 Pressure	Bar	1959
V19	Low Temp SuperHeater Left Wall Outlet Before superheater dryer	°C	704
V20	Low Temp SuperHeater Right Wall Outlet Before superheater dryer	°C	2612
V21	Low Temp SuperHeater Left wall After superheater dryer	°C	958
V22	Low Temp SuperHeater Right Wall Exchange Metal Temp	°C	2474
V23	Intermediate SuperHeater Exchange Metal Temp	°C	1948
V24	Intermediate SuperHeater Outlet Before superheater dryer	°C	1944
V25	Intermediate SuperHeater Outlet Header Metal Temp	°C	2007
V26	High Temp SuperHeater Outlet Header Metal Temp	°C	2480
V27	High Temperature ReHeater Outlet Steam Press	Bar	2477
V28	Superheated Steam From Intermediate Outlet Pressure	Bar	-
V29	Superheater Water Injection Compensated Flow	Ton/Hr	-
V30	Economiser Inlet Pressure	Bar	961
V31	Economiser Inlet Temp	°C	-
V32	Economiser Outlet Temp	°C	-
TI	V5, V8, V9, V11, V14, V17, V20, V22, V26, V27		
TMI	V20		

After identifying and assuming the very important variable which is "*Low Temp Superheater Right Wall Outlet Before Superheater Dryer*", the data will be fed into the real ANN model for further rationalization to obtain the acceptable and justified results. Based on the figure 4.1 below, the behavior of the data for the first 200 minutes of operation is very steady eventhough there are sensors that had detected faults. However, after the sensors at "*Low Temp Superheater Right Wall Outlet Before Superheater Dryer*" (V20) detect faults after 2612 minutes of operations, the unit shutdown 3 minutes later.

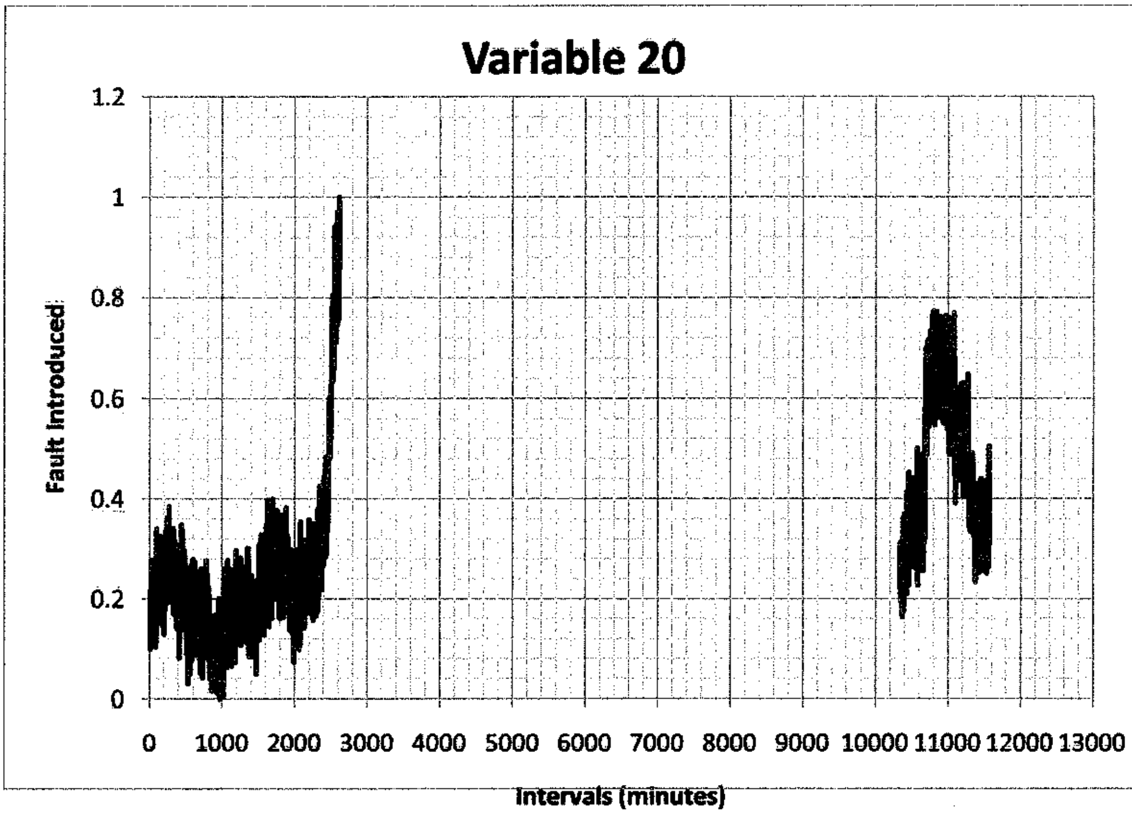


Figure 4.1 Variable of Low Temp Superheater Right Wall Outlet Before Superheater Dryer

Next step of this study is to model the NN network to produce a NN model that finally can forecast the trip earlier before the real shutdown for the ease of operator to take appropriate actions to avoid the shutdown. The data selected based on the 32 variables and fed into the NN model whereby the data is the normalized data which consists of all data before the real shutdown. This step is crucial since the primary objective is to forecast the trip before the real shutdown. The data undergone training and validation and there are 2 types hidden layers are used. First model is constructed by using only one (1) hidden layer with 10 neurons and the other model is constructed by using 2 hidden layers with 10 neurons. The neurons used in the model are only up to 10 neurons because the RMSE will be much higher than 0.5 and even up to 1.0 if using more than 10 neurons. The reason of using only 1 and 2 hidden layers is because the RMSE for 3 or more hidden layers will be constant. Hence, the ANN model is simulated with only up to 2 hidden layers.

For model with 1 hidden layer, there are two types of activation functions that had been combined together and used. The combinations are *purelin* and *logsig* (P+L), *tansig* and *logsig* (T+L), *purelin* and *tansig* (P+T) and so on. There are about 9 combinations of activation functions that had been simulated in this 1 HL model. Each combination will produced different root mean square errors (RMSE) under 1 neuron up to 10 neurons. Hence, the smallest RMSE produced under certain combination of activation function and certain neurons will be taken as the best combination for respective training algorithms.

For 2 HL model, there are 27 combinations of activation functions that had been simulated and each combination produced different values of RMSE. However, the ANN model is constructed with only 1 and 2 hidden layers because the 3 hidden layers model are constantly producing the value of RMSE which similar to the model with 2 hidden layers.

Each combination of the activation functions are simulated under different training algorithms because each training algorithms producing different functions as mentioned in the introduction part previously. Below are the data that has been tabulated and also has been compared by using comparison graph for the ease of analysis.

[illegible]																				
L+L	0.513	0.510	0.535	0.490	0.486	0.510	0.537	0.565	0.474	0.456	0.513	0.537	0.537	0.518	0.537	0.537	0.536	0.536	0.536	0.536
L+T	0.463	0.468	0.457	0.499	0.691	0.467	0.468	0.472	0.443	0.622	0.583	0.560	0.554	0.533	0.585	0.495	0.624	0.679	0.508	0.483
L+P	0.522	1.614	0.522	0.561	0.534	0.487	2.905	0.524	11.154	0.505	0.541	0.842	0.582	0.530	0.539	0.538	0.585	0.524	0.623	0.582
T+T	0.501	0.539	0.479	0.582	0.533	0.506	0.619	0.463	0.586	0.871	0.526	0.637	0.532	0.543	0.522	0.523	0.545	0.581	0.505	0.509
T+L	0.504	0.504	0.470	0.460	0.536	0.512	0.547	0.463	0.478	0.456	0.536	0.507	0.525	0.536	0.536	0.535	0.536	0.500	0.525	0.522
T+P	0.511	0.518	0.525	0.551	0.540	0.537	0.589	5.558	4.272	1.396	0.669	0.546	0.514	0.522	0.746	0.508	0.605	0.522	0.516	0.542
P+P	0.763	0.785	0.764	0.763	0.763	0.763	0.763	0.725	0.763	0.763	0.580	0.558	0.529	0.539	0.594	0.570	0.468	0.536	0.534	0.559
P+L	0.463	0.517	0.569	0.527	0.521	0.787	0.493	0.486	0.491	0.503	0.534	0.535	0.535	0.536	0.536	0.536	0.524	0.534	0.536	0.537
P+T	0.588	0.594	0.586	0.589	0.596	0.878	0.593	0.844	0.844	0.596	0.585	0.511	0.570	0.638	0.568	0.563	0.606	0.601	0.612	0.509
[illegible]																				
L+L	0.530	0.486	0.524	0.524	0.472	0.465	0.537	0.504	0.501	0.536	0.449	0.462	0.536	0.524	0.499	0.433	0.535	0.481	0.537	0.474
L+T	0.497	0.513	0.511	0.534	0.568	0.487	0.650	0.499	0.504	0.606	0.513	0.507	0.536	0.607	0.603	0.559	0.539	0.497	0.511	0.596
L+P	0.522	0.534	2.427	0.486	0.481	0.757	0.520	0.553	2.888	0.501	0.542	0.538	0.576	0.521	0.529	0.593	0.525	0.539	0.500	0.589
T+T	0.498	0.521	0.527	0.492	0.441	0.480	0.459	0.490	0.471	0.447	0.500	0.613	0.632	0.724	0.586	0.584	0.734	0.585	0.549	0.579
T+L	0.513	0.500	0.506	0.457	0.465	0.460	0.467	0.514	0.537	0.507	0.517	0.518	0.464	0.520	0.464	0.460	0.526	0.521	0.511	0.529
T+P	0.530	0.512	0.459	0.508	0.711	0.474	0.465	3.342	0.488	0.489	0.515	0.528	0.661	0.520	0.645	0.619	0.501	0.525	0.604	0.518
P+P	0.569	0.638	0.625	0.522	0.733	0.923	0.730	0.815	0.782	0.671	0.562	0.579	0.564	0.587	0.509	0.550	0.520	0.535	0.503	0.537
P+L	0.537	0.478	0.486	0.507	0.536	0.498	0.535	0.466	0.467	0.537	0.450	0.472	0.536	0.498	0.470	0.482	0.536	0.537	0.531	0.473
P+T	0.699	0.688	0.555	0.724	0.698	0.666	0.738	0.675	0.616	0.657	0.562	0.523	0.561	0.590	0.569	0.578	0.544	0.545	0.592	0.606

Table 4.2 RMSE for training functions of 1 hidden layer

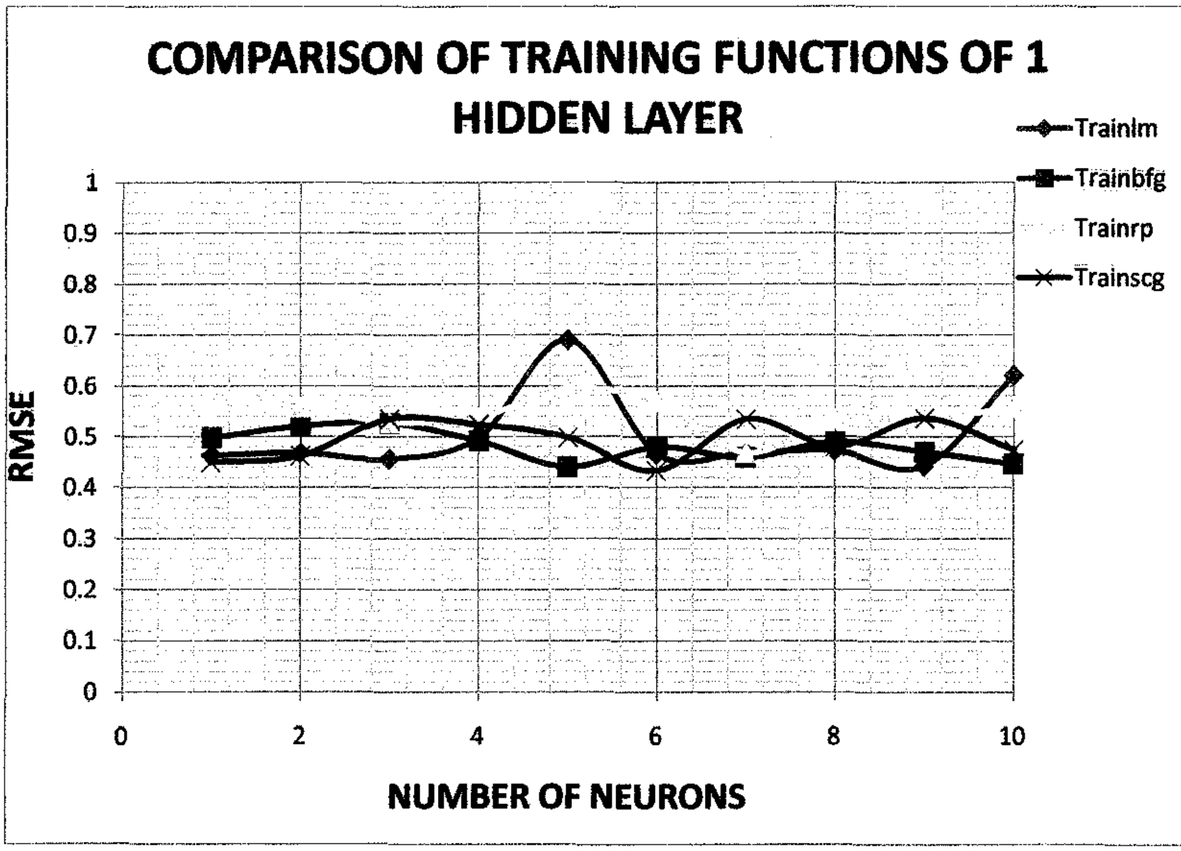


Figure 4.2 Comparison of training functions of 1 hidden layer

Above is the graph of the comparison of training functions of 1 hidden layer which produced different RMSE under the combination of 2 activation functions from 1 neuron up to 10 neurons. This graph is for the ease of selection of the best training algorithm and combination of activation functions which produced the smallest RMSE.

Based on the data of root mean square error (RMSE) tabulated for each training algorithms, the best training algorithm for 1 hidden layer is ***trainscg*** with the combination of ***logsig*** and ***logsig*** (L+L) activation functions. Under the combination of "L+L" activation functions with up to 6 neurons, the ***trainscg*** had produced the smallest RMSE of 0.4335005 among all of the small RMSE produced.

Next is to select the best combination of activation function and training algorithm of 2 hidden layers model which produced the smallest RMSE.

NNHL2	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
NNHL1	T+T+T					Trainlm					P+T+L					Trainscg				
1	0.501	0.511	0.494	0.516	0.491	0.477	0.516	0.516	0.509	0.515	0.513	0.544	0.507	0.505	0.525	0.519	0.530	0.514	0.527	0.465
2	0.535	0.537	0.537	0.491	0.516	0.524	0.566	0.537	0.716	0.502	0.529	0.535	0.513	0.528	0.507	0.532	0.546	0.439	0.459	0.518
3	0.495	0.641	0.513	0.536	0.555	0.474	0.687	0.557	0.484	0.478	0.513	0.513	0.474	0.525	0.579	0.526	0.460	0.497	0.527	0.508
4	0.741	0.505	0.650	0.464	0.565	0.496	0.481	0.486	0.482	0.522	0.452	0.533	0.537	0.523	0.508	0.528	0.513	0.534	0.515	0.522
5	0.459	0.531	0.480	0.530	0.578	0.523	0.511	0.440	0.495	0.468	0.513	0.504	0.515	0.513	0.513	0.537	0.534	0.524	0.503	0.506
6	0.466	0.494	0.475	0.595	0.773	0.503	0.721	0.651	0.886	0.472	0.527	0.513	0.463	0.467	0.525	0.525	0.475	0.515	0.454	0.496
7	0.544	0.480	0.514	0.650	0.622	0.616	0.520	0.707	0.637	0.487	0.513	0.535	0.515	0.536	0.529	0.529	0.503	0.510	[redacted]	0.448
8	0.756	0.765	0.719	0.844	[redacted]	0.615	0.844	0.492	0.522	0.526	0.513	0.517	0.471	0.491	0.528	0.472	0.502	0.455	0.531	0.498
9	0.498	0.640	0.694	0.624	0.596	0.476	0.493	1.005	0.447	0.575	0.513	0.522	0.534	0.514	0.528	0.531	0.531	0.531	0.535	0.517
10	0.495	0.902	0.458	0.470	0.524	0.562	0.684	0.653	0.527	0.510	0.513	0.460	0.535	0.531	0.475	0.533	0.510	0.507	0.531	0.515
NNHL1	T+T+L					Trainrp					L+T+L					Trainbfg				
1	0.524	0.533	0.535	0.531	0.529	0.513	0.506	0.529	0.537	0.534	0.527	0.475	0.537	0.513	0.537	0.513	0.537	0.513	0.459	0.525
2	0.512	0.527	0.533	0.513	0.536	0.532	0.536	0.536	0.531	0.534	0.537	0.537	0.537	0.513	0.489	0.462	0.520	0.537	0.536	0.533
3	0.513	0.512	0.535	0.536	0.535	0.532	0.522	0.537	0.529	0.539	0.536	0.491	0.513	0.467	0.536	0.452	0.480	0.537	0.460	0.496
4	0.513	0.533	0.531	0.536	0.519	0.536	0.536	0.536	0.537	0.537	0.461	0.471	0.537	0.534	0.468	0.460	0.537	0.518	0.537	0.508
5	0.536	0.535	0.524	0.533	0.533	0.536	0.536	0.536	0.528	0.514	0.487	0.494	0.537	0.529	0.536	0.502	0.496	0.537	0.535	0.485
6	0.537	0.512	0.522	0.530	0.535	0.537	0.506	0.448	0.536	0.528	0.526	0.537	0.497	0.516	0.474	0.537	0.532	0.537	0.529	0.508
7	0.536	0.536	0.535	0.537	0.536	0.529	0.534	0.496	0.483	0.537	0.495	0.514	0.529	0.537	0.537	0.523	0.506	0.524	0.505	0.530
8	0.537	0.533	0.510	0.537	0.536	0.487	0.519	0.532	0.473	0.535	0.536	0.487	0.463	0.529	0.534	0.535	0.537	0.537	0.537	0.504
9	0.531	0.537	0.534	0.535	[redacted]	0.528	0.537	0.534	0.536	0.537	0.452	0.536	0.453	[redacted]	0.536	0.534	0.536	0.537	0.536	0.537
10	0.537	0.533	0.533	0.536	0.535	0.532	0.531	0.537	0.537	0.508	0.491	0.474	0.456	0.537	0.537	0.537	0.537	0.523	0.537	0.490

Table 4.3 RMSE for training functions of 2 hidden layers

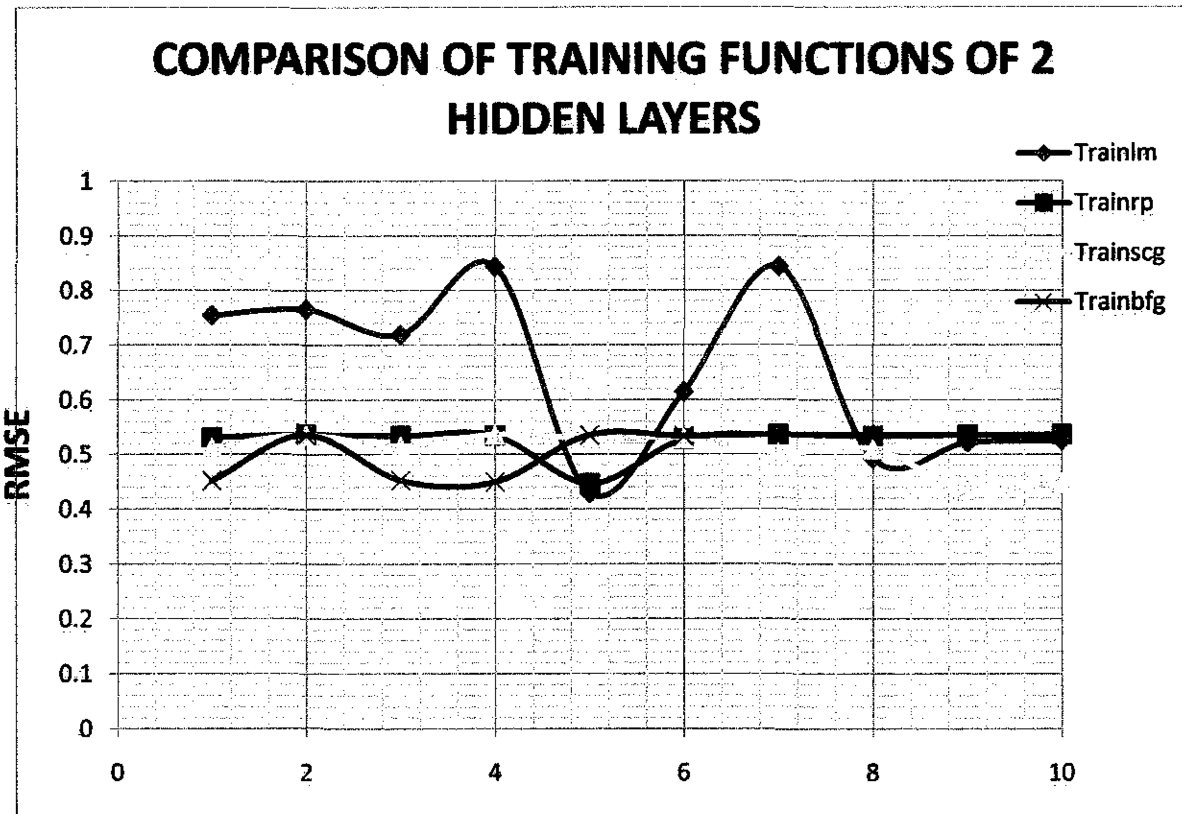


Figure 4.3 Comparison of training functions of 2 hidden layers

Training Algorithm	Trainrp	Trainlm	Trainscg	Trainbfg
RMSE	0.446	**0.429**	0.434	0.449
Architecture	9HL1-5HL2	**8HL1-5HL2**	7HL1-9HL2	9HL1-4HL2

Table 4.4 The Best Combination For FDDNN Models.

The graphs tabulated above is the graph of the comparison of training functions of 2 hidden layers which had produced root mean square errors under the combination of 3 activation functions (*purelin, logsig* and *tansig*). There are 27 combinations of activation functions that been simulated for each training algorithms. Based on the data of root mean square error (RMSE) tabulated for each training algorithms, the best training algorithm for 2 hidden layer2 is ***trainlm*** with the combination of *tansig, purelin* and *tansig* (T+P+T) activation functions. Under the combination of "T+P+T" activation functions with 8 neurons in 1 hidden layer and 5 neurons in 2 hidden layers, the ***trainlm*** had produced the RMSE value of 0.429.

After the comparison of the best training algoritms in 1 hidden layer model and 2 hidden layers model, the ***trainlm*** in 2 hidden layers model which produced the smallest is chosen to undergo the next step which is the validation step whereby in this step, the model will simulated by using different coding to finally produced the final forecasted graph which is important to prove that the trips are able to be forecasted earlier before the real shutdown. The graph below represents the forecasted graph whereby the forecast trip is known as the "Actual RMSE" and the real trip is known as "Predicted RMSE".

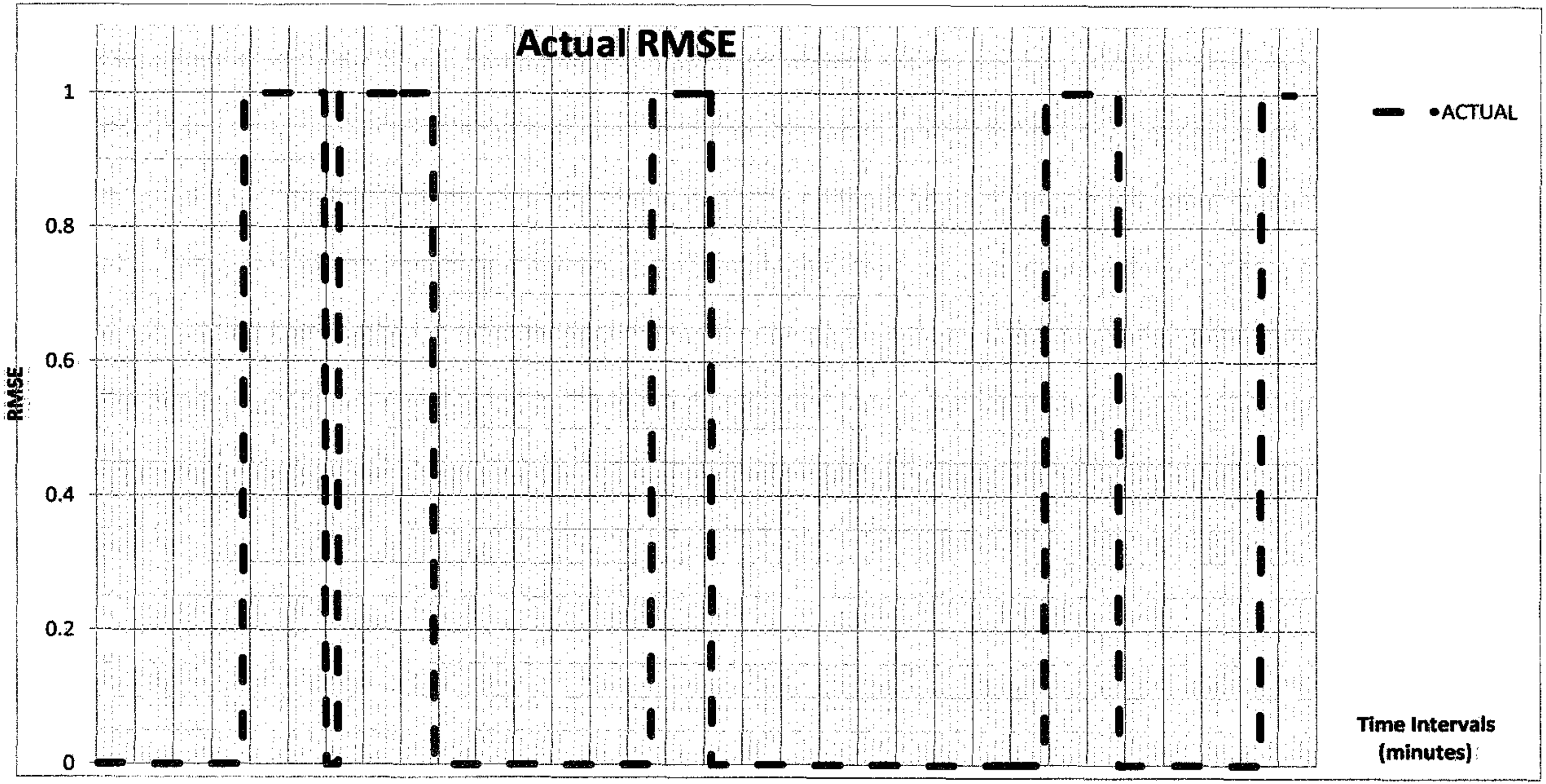


Figure 4.4 Actual RMSE

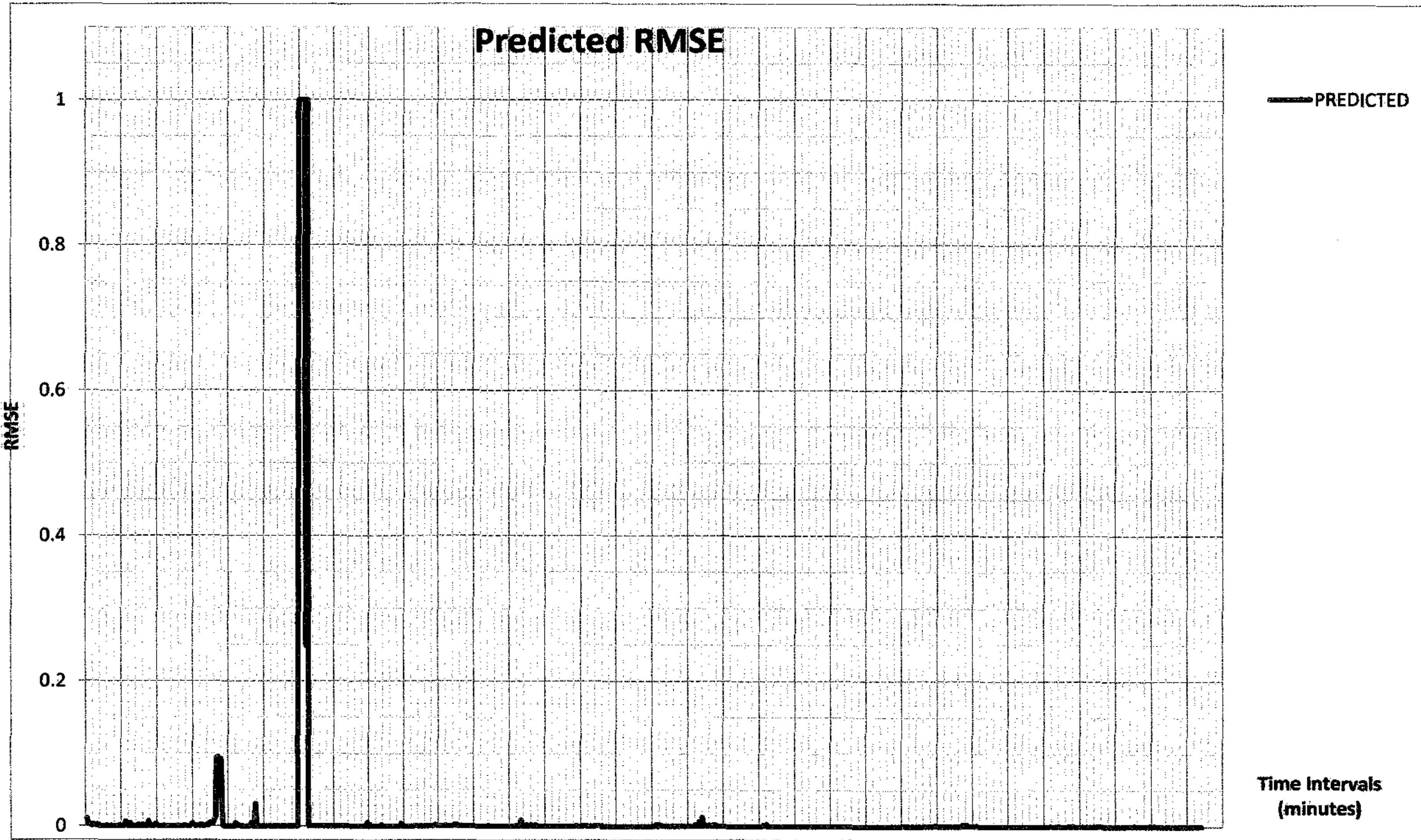


Figure 4.5 Predicted RMSE

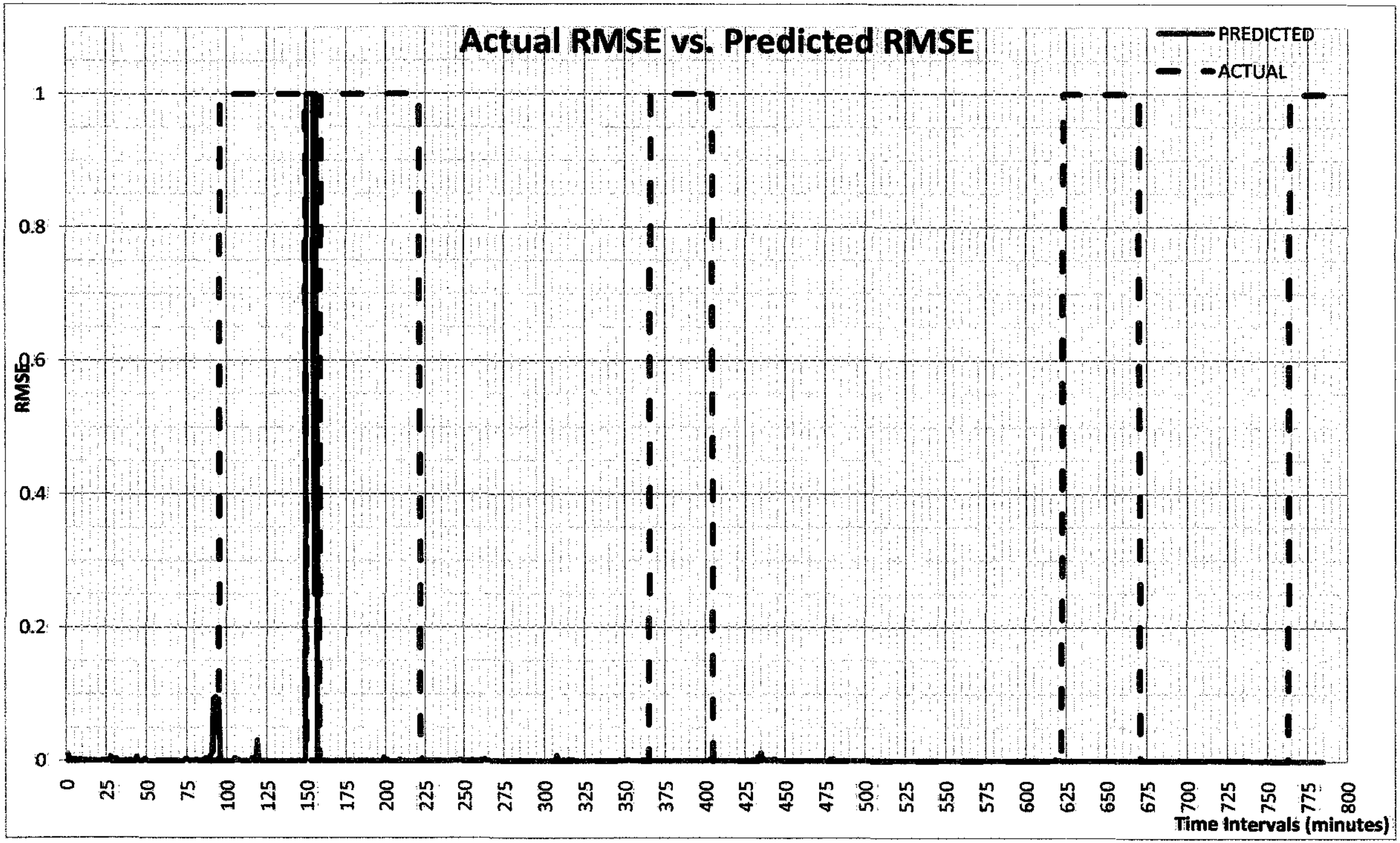


Figure 4.3 Actual RMSE vs. Predicted RMSE

As discussed above, the two models are quite similar though they have slightly different RMSE. Regarding accuracy, model with 2 hidden layers produced better RMSE whereby model with 1 hidden layer is slightly better. Since NN model with 2 hidden layers produced the smallest RMSE, hence it is chosen to undergo the validation process whereby the process is to validate the steps before and finally came up with the forecasting graph which consists of the predicted output and actual output. The predicted output is the forecast model which is essential to occur before the actual output whereby the output is the real trip which occurs.

Without implementing this ANN system, the trip will continuously occur as shown in figure 4.4. In the graph, the trip will eventually occur for every 200 minutes of operation and this will affect the plant operations. The graph shown in figure 4.5 is the predicted (forecast) trip that will ultimately occur before the real trip. This forecast trip will actually help the plant operator to take premature or prevention actions to prevent the real trip that will occur after a few minutes.

Based on the graph above, the predicted (forecast) trip in blue lines occurs after 150 minutes of operation whereby it can forecast the trip about 10 minutes earlier before the real trip (red lines) which occur after 160 minutes of operation. The data is classified as trip once it reaches the trip value ('1'). The difference between the actual and predicted RMSE is essential and has been prove in this study that with the gap of 10 minutes, the real trip is possible to be eliminated or avoided which will ensure the boiler unit running continuously. Since this ANN system is a continuous-learning system, the future trip that will occur in the future can be forecasted again since the ANN system will detect it earlier.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

Based on the study findings and justifications from other researchers on Artificial Neural Network, it is well-known that by developing the methodology of the neural network in the research, a significant improvement in the process can be achieved. Neural Networks are useful whenever a nonlinear relation between numerical data is sought.

The objective of the ANN model was to forecast the trip of the boiler unit based on the suitable combination of input parameters. Acquired data from the plant, their processing and proper selection of training data are discussed in details. Agreement between the data and NN results is excellent and it is also pointed out the NN is a strong tool for monitoring.

The results of ANN are very sensitive to number of neurons. It might have different result in each run even with fixed number of neurons. Increasing the number of neurons in hidden layer will decrease the number of calculation steps with subsequent decrease in the root mean square error.

The variable "*Low Temp Superheater Right Wall Outlet before Superheater Dryer*" (V20) is assumed to be the main contributor to the shutdown. However, this study only focuses on studying and identifying the behavior of the variables and the ANN modeling instead of confirming the main contributor. For the recommendation for future works, the knowledge gained in developing this set of NN will serve as the ground work for the future development and validation of other artificial intelligence systems to minimize the effect of boiler tube leakage.

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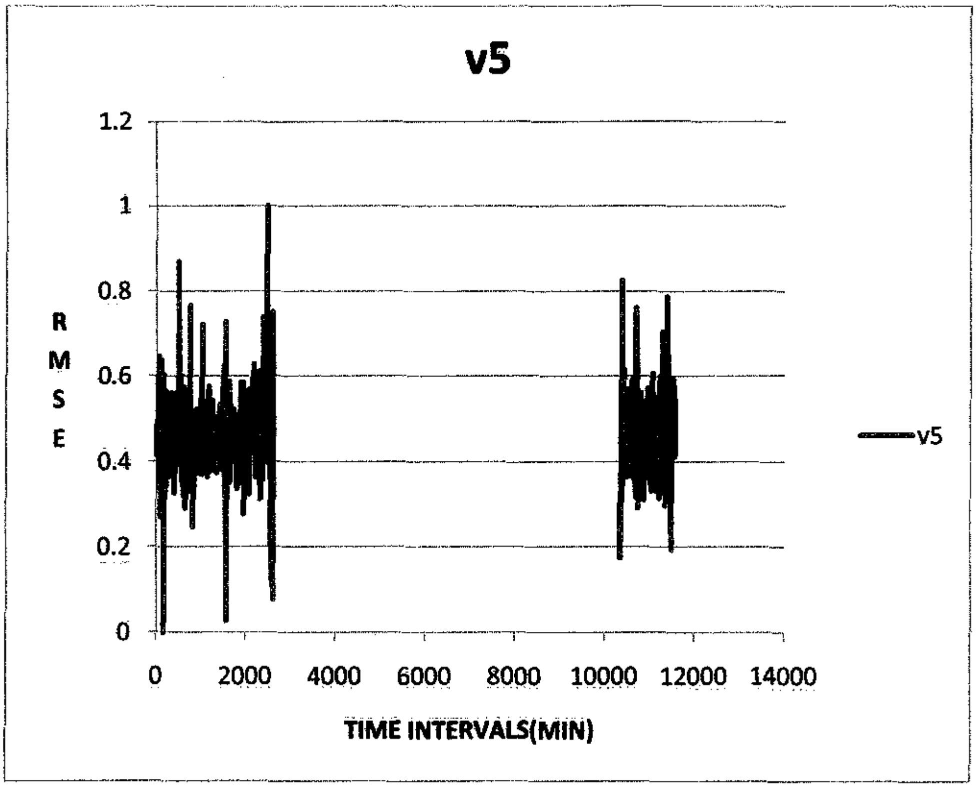
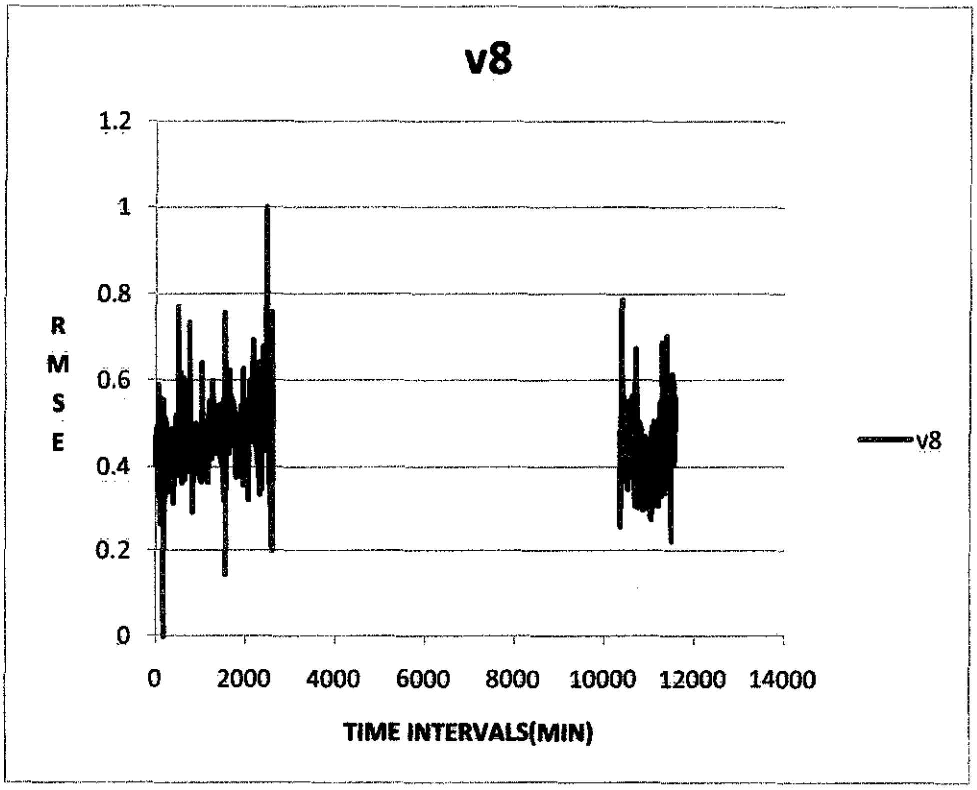
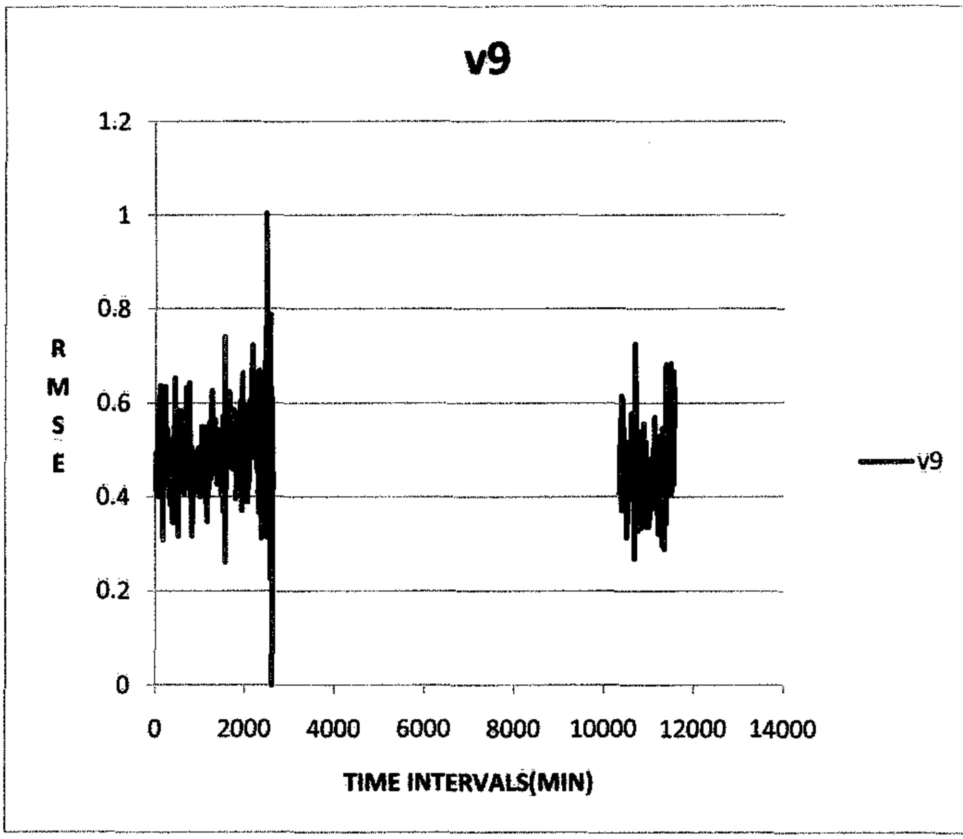
The influenced parameters



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0.6
0.4
0.2
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M
S
E
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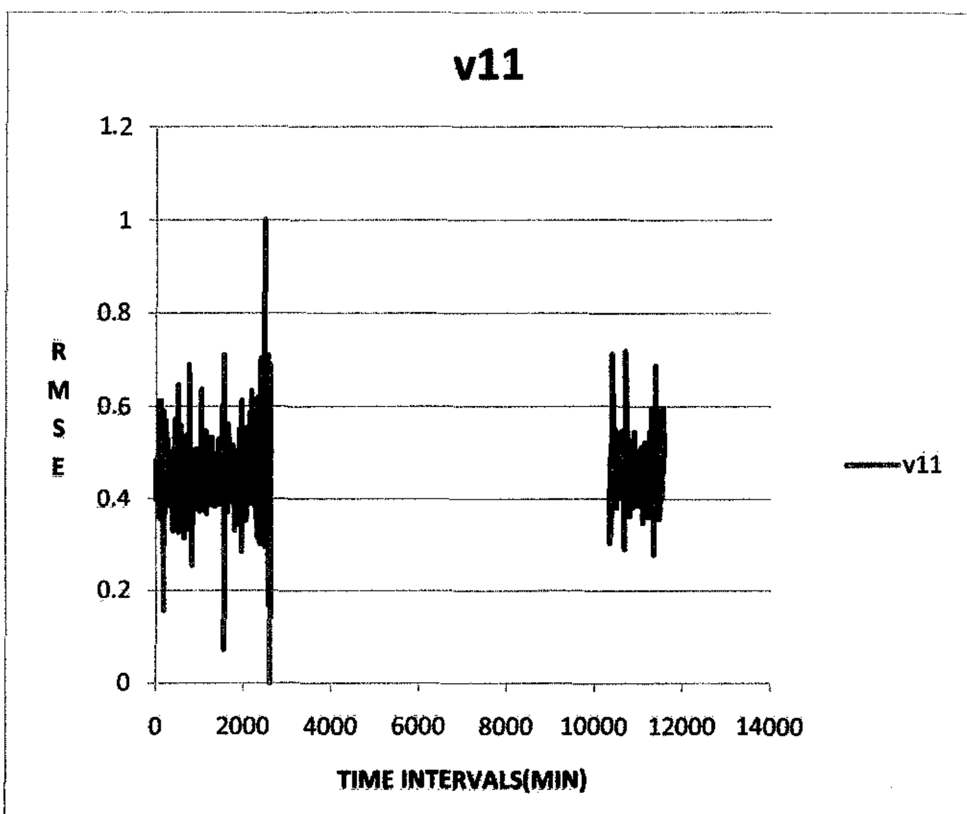
4000
6000
8000
10000
12000
14000
TIME INTERVALS(MIN)
v9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0.8
0.6
0.4
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R
M
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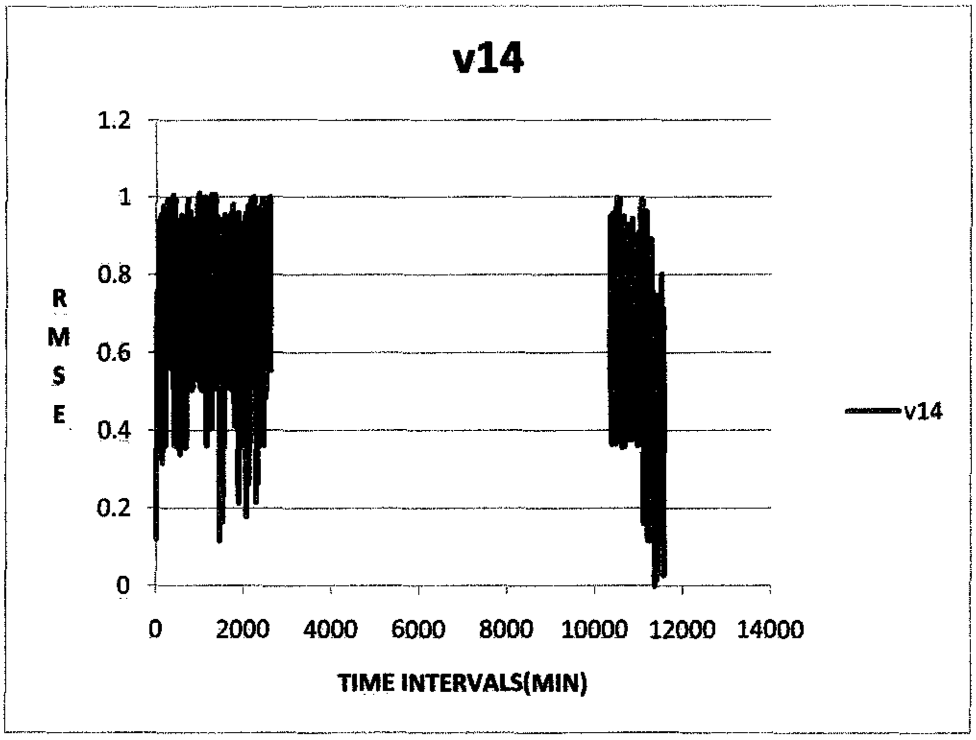
10000
12000
14000
TIME INTERVALS(MIN)
v11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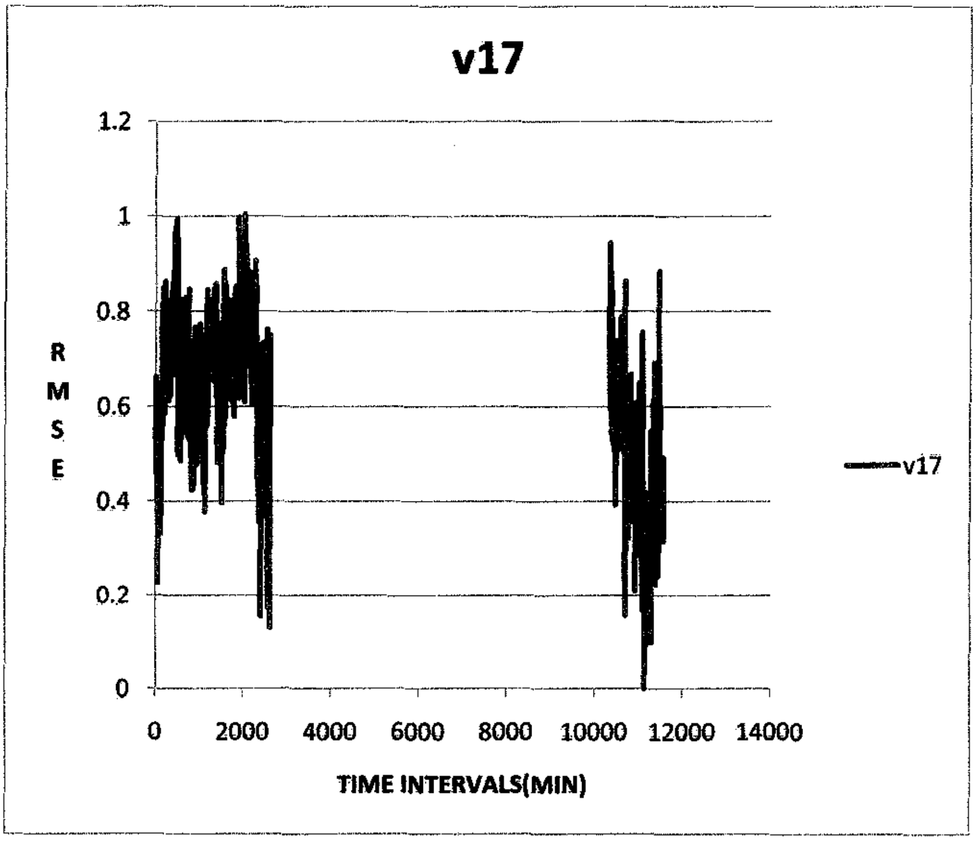
TIME INTERVALS(MIN)
v14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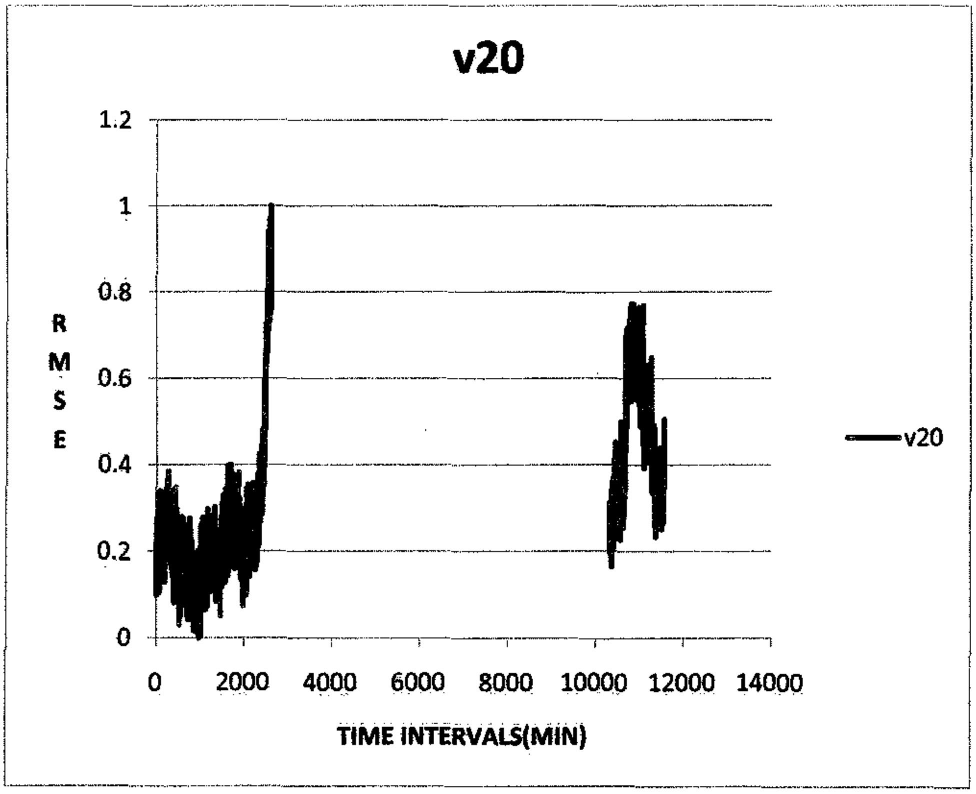
14000
TIME INTERVALS(MIN)
v17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0.8
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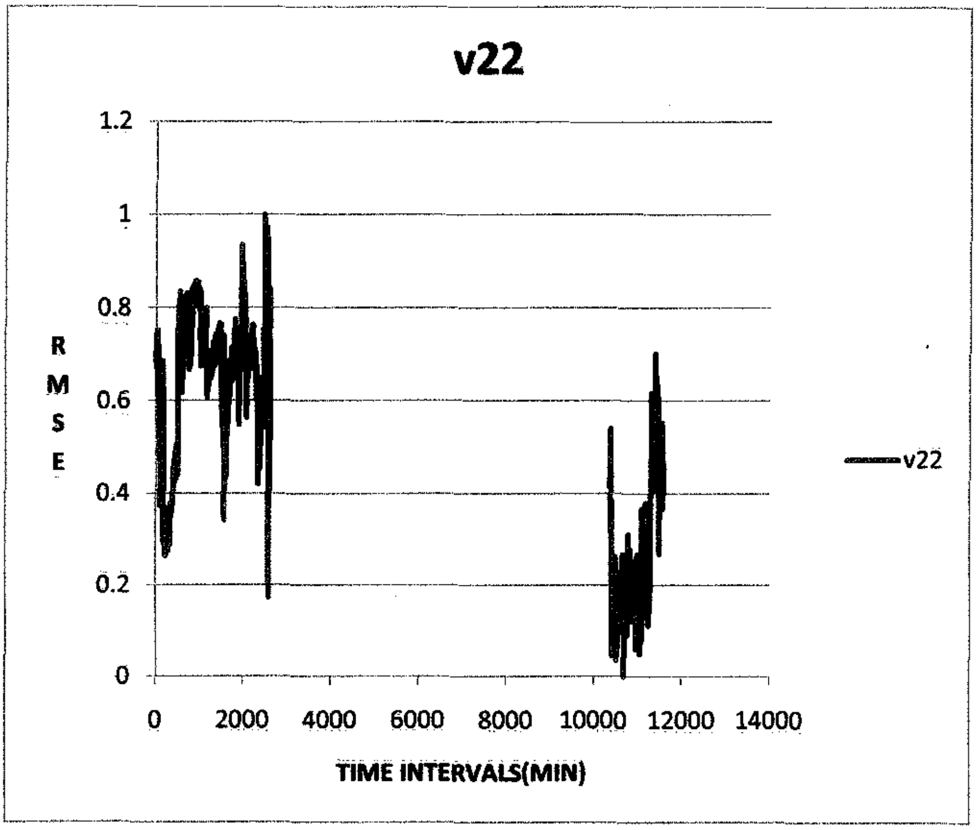
R M S E
0 2000 4000 6000 8000 10000 12000 14000
TIME INTERVALS(MIN)
v20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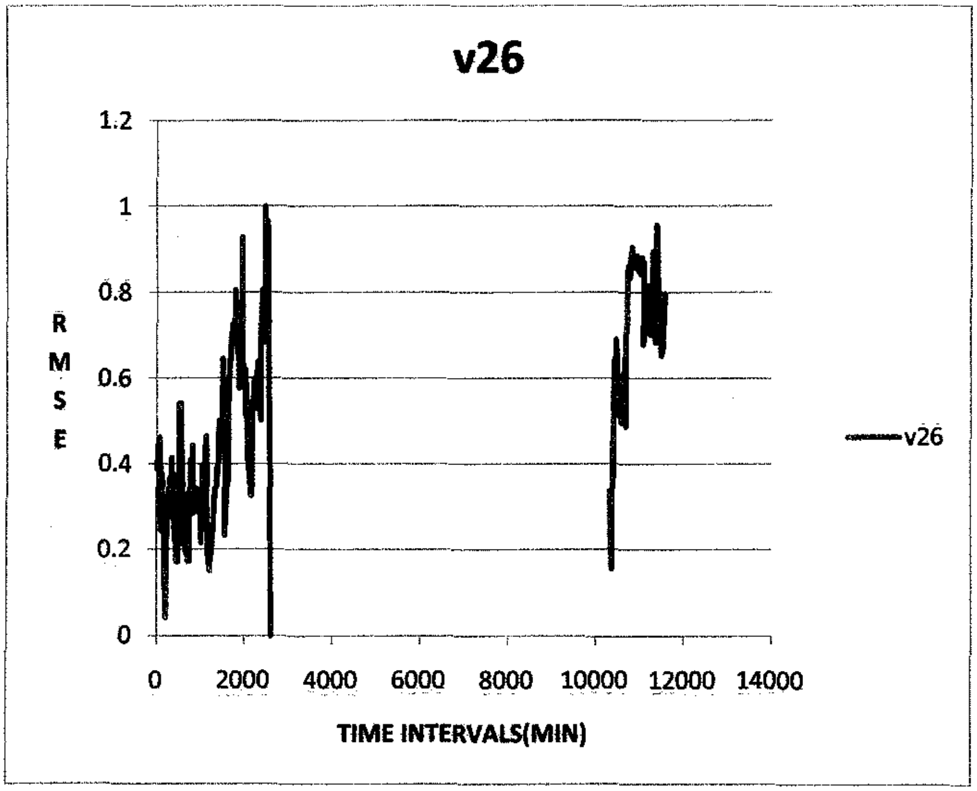
1
0.8
0.6
0.4
0.2
0
R M S E
0 2000 4000 6000 8000 10000 12000 14000
TIME INTERVALS(MIN)
v22


v26
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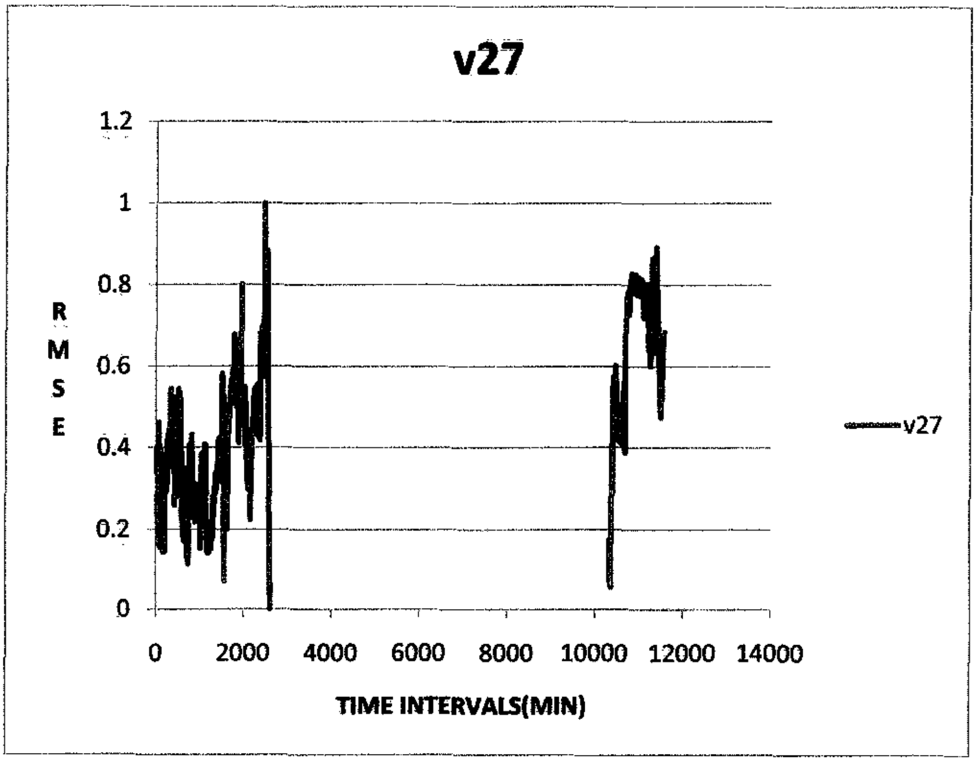
1
0.8
0.6
0.4
0.2
0
R M S E
0
2000
4000
6000
8000
10000
12000
14000
TIME INTERVALS(MIN)
v26


v27
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1
0.8
0.6
0.4
0.2
0
R M S E
0
2000
4000
6000
8000
10000
12000
14000
TIME INTERVALS(MIN)
v27

Gantt Chart FYP I

ID	Task Name	Duration	Start	Finish	JULY			AUGUST				SEPTEMBER				OCTOBER			
					21	28	30	7	14	21	28	7	14	21	28	7	14	21	28
		125days	**25-Jul**	**31-Oct**															
1	**Selection Of The Topic**	7 days	25-Jul	1-Aug															
2	**Literature Review**	21 days	2-Aug	23-Aug															
3	**Submission of Preliminary Report**	1 day	14-Aug	14-Aug															
4	**Thermal Power Plant Boiler NN Model and Training Algorithm Fault Detection & Diagnosis Literature Review**	21 day	2-Aug	23-Aug															
5	**NN Model and Training Algorithm**	21 day	2-Aug	23-Aug															
6	**Fault Detection & Diagnosis**	21 day	2-Aug	23-Aug															
7	**Submission of Progress Report and Seminar**	1 day	9-Sep	9-Sep															
8	**Data Preparation, Modeling, Simulation and Analysis**	30 day	27-Aug	27-Sep															
9	**Submission of Interim Report Final Draft**	1 day	13-Oct	13-Oct															
10	**Oral Presentation**	1 day	28-Oct	28-Oct															

Gantt Chart FYP II

ID	Task Name	Duration	Start	Finish
		103days	**25-Jan**	**9-Apr**
1	**Understanding NN MATLAB Toolbox**	14 days	25-Jan	7-Feb
2	**Understanding NN Topologies**	14 days	7-Feb	21-Feb
3	**Submission of Progress Report 1**	1 day	22-Feb	22-Feb
4	**Trial &error approach NN Modeling for 1 hidden layer**	14 day	23-Feb	3-Mar
5	**Trial &error approach NN Modeling for 2 hidden layers**	14 day	3-Mar	10-Mar
6	**Validation of NN modeling with 1 hidden layer**	14 day	11-Mar	25-Mar
7	**Validation of NN modeling with 2 hidden layers**	20 day	25-Mar	8-Apr
8	**Submission of Progress Report 2**	1 day	22-Mar	22-Mar
9	**Seminar**	1 day	29-Mar	29-Mar
10	**Poster Exhibition**	1 day	12-Apr	12-Apr
11	**Analysis & Results**	7days	8-Apr	15-Apr
12	**Submission of Dissertation Final Draft**	1 day	4-May	4-May
13	**Oral Presentation**	1 day	10-May	10-May

JANUARY			FEB				MARCH			APRIL			MAY			
21	28	30	7	14	21	28	14	21	28	14	21	28	7	14	21	28