NEURAL NETWORK PREDICTION MODEL OF ENERGY CONSUMPTION FOR BILLING INTEGRITY

By

NURUL HAMIZA BINTI ZAHARULHISHAM

FINAL PROJECT REPORT

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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Approved:

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Project Supervisor

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK

MAY 2011

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.

NURUL HAMIZA BINTI ZAHARULHISHAM

ABSTRACT

Neural networks for the real world applications are increasing rapidly. Artificial Neural Network is a system loosely modeled based on the human brain. It has ability to account for any functional dependency. The network discovers by learning and modeling the nature of the dependency without needing to be prompted. Nowadays, neural networks are a powerful technique to solve many real world problems. They have the ability to learn from experience in order to improve their performance and to adapt themselves to the changes in the environment. Furthermore, they are able to deal with incomplete information or noisy data and can be very effective especially in situations where it is not possible to define the rules or steps that lead to the solution of a problem. This report contains five chapters which are the introduction, literature review methodology, results and discussions and the conclusion. In the first chapter, the introduction explains about the background study, problem statement and also the main objectives of the project. The main objective of the project is to develop a neural network model to predict energy consumption for billing integrity. The second chapter of this report stated the theory and literature review of the neural network. The literature review is taken mostly from journals of many previous studies about neural network. Next, the third chapter explains about the methodology of the project. Under the methodology section, the author includes a project activities flow chart and also explains about the tools required to execute the project. This project is carried out in two semesters. The milestone for the project work is presented nicely in a Gantt chart. Then, in the results and discussion chapter, the author stated about the neural network model developed using MATLAB. Last but not least, the conclusion recommendations for the model improvement.

ACKNOWLEDGEMENT

First of all, I would like to thank Allah the Almighty who has given me strength and blessings to complete my two semesters of Final Year Project. The utmost gratitude goes to my supervisor, Dr. Rosdiazli Ibrahim for his continuous guidance and support throughout my project. I would also like to give appreciation to Ms. Maryam Jamela Ismail who has been a great teacher, and helping me getting through many challenges during this project. Besides that, I would like to thank Universiti Teknologi PETRONAS (UTP), especially the Electrical and Electronics Engineering Department whereby students are given the opportunity to experience doing research or design work. It is an opportunity for us, students to use the tools and techniques for problem-solving. Furthermore, the learning process is gained through hands-on experience. Last but not least, thank you to all my fellow friends and family for their love and support, I have successfully completed my Final Year Project.

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CHAPTER 1
INTRODUCTION

1.1 Background of Study

In the oil and gas industry, accurate measurement of liquids and gases are vital to the concern of the products sold and returned as money worth product to seller and buyer. The existing system in Transmission Operation Division (TOD), PETRONAS Gas Berhad (PGB), Gurun is responsible to calculate the energy consumption from the sales gas produced. The system is a composition of a turbine meter, measuring equipments which are the pressure and temperature transmitter, gas chromatography, and flow computer. Several inputs obtained from the measuring equipments are used to calculate the energy consumption. The inputs are pressure, temperature, gross volume, calorific value and specific gravity. The consistency and reliability of the system must be ensured to maintain the billing integrity in PETRONAS Gas Berhad.

An energy prediction model will be developed to compare the results with the existing metering system in TOD, PGB to ensure the integrity of the system. For this project, the tool to be used is the neural network prediction model. An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the biological nervous system, in this case, the brain to process information. It is capable to learn the data patterns within a multi-dimensional information domain. The neural network model will be used to analyse the performance, forecast the energy consumption and also to construct a much more reliable metering system for billing integrity in PETRONAS.

1.2 Problem Statement

The existing metering system in TOD, PGB is a standalone system that does not have a reference system in order to verify the integrity of the system itself. This means that, there are no other alternative system to compare and verify the accuracy and consistency of the calculated energy and the end sales gas transmitted. The calculation of gas volume is based on American Gas Association (AGA) equation. However, in actual condition, temperature and pressure varies. Furthermore, there are some uncertainties and variables that are not captured in the equation. This is where problem occurs when the reading of sales gas volume received by the customer varies from the sales gas volume that is transmitted from TOD.

In PETRONAS Gas Berhad, TOD holds the responsibility for all activities that relates to the gas transmission to all end customers. TOD has carried out many initiatives to ensure safe and efficient delivery of products through the pipeline. However, problems like stated above affect the reliability of PETRONAS' metering system and business credibility.

1.3 Objectives and Scope of Study

- To develop a neural network model prediction of energy consumption for billing integrity.
- The model is developed using Artificial Neural Network (ANN) whereby the ANN will learn the relations between input parameters, controlled and uncontrolled variables by studying the previous recorded data.
- The model will predict the output based on the trained data earlier for other input.
- To integrate the developed model as part of the system that can be utilised as a tool for billing integrity.
- The scope of study revolves around the neural network model and architecture, hence, applying it for this project.

1.3.1 Significance of Project

- The developed neural network model will compare energy consumption data with the existing system data. A reliable model will manage to produce accurate readings that are less than 1% error of energy prediction.
- The developed neural network will also be able to predict energy consumption even when there are any missing input parameters.
- The successful model will reduce dispute between end customer and PETRONAS Gas Berhad (PGB).
- The integrity and reliability of PETRONAS' metering system will be maintained, gas transmission to end customer smoothens, thus enhanced profits to the distributor.

CHAPTER 2
LITERATURE REVIEW

2.1 Artificial Neural Network

An Artificial Neural Network (ANN) is system based on the operation of biological neural networks. It is composed of a large number of interconnected processing elements (neurones) that works in unison to solve specific problems. ANN is like people whereby it learns by example. Neural networks can be configured to perform many tasks that include pattern recognition, data mining, forecasting and process modelling [2]. Neural network can be considered as a black box that is able to predict an output pattern when it recognizes a given input pattern. Once trained, the neural network is able to recognize similarities when presented with a new input pattern, resulting in a predicted output pattern [1].

The notion of memory is hypothesized in the biological network to be in the synaptic connections. Based on this hypothesis, the values or weights, of the connection strengths determine the 'memory', or 'knowledge' of the neural network. Most neural networks go through a 'learning' procedure during which the network weights are adjusted. Algorithms for varying these connection strengths or weights such that learning ensues are called 'learning rules'. The learning may be 'supervised', in which case the network is presented with target answers for each pattern, or, learning is 'unsupervised' and the neural network adjusts its weights in response to input patterns without the benefit or target outputs. In such networks, the network classifies the input patterns into similarity categories [3].

A huge number of researchers have applied ANN in their work that revolves around prediction of energy consumption [4]. The latest technology in neural network was the neural networks built for image recognition are well-suited for "seeing" sound. Students at the University of Hong Kong describes a novel use of neural networks, collections of artificial neurons or nodes that can be trained to accomplish a wide variety of tasks, previously used only in image recognition. The students used a convolutional network to "learn" features, such as tempo and harmony, from a database of songs that spread across ten genres. The result was a set of trained neural networks that could correctly identify the genre of a song, which in computer science is considered a very hard problem, with greater than 87 percent accuracy. The group won an award for best paper at the International Multiconference of Engineers and Computer Scientists [5].

2.2 Neural Network Architecture

The neural networks have inputs where it will be adjusted or trained, so that a particular input results to a specific output. The figure below shows that the network is adjusted based on a comparison of the output and the target, until the network output matches the target [6].

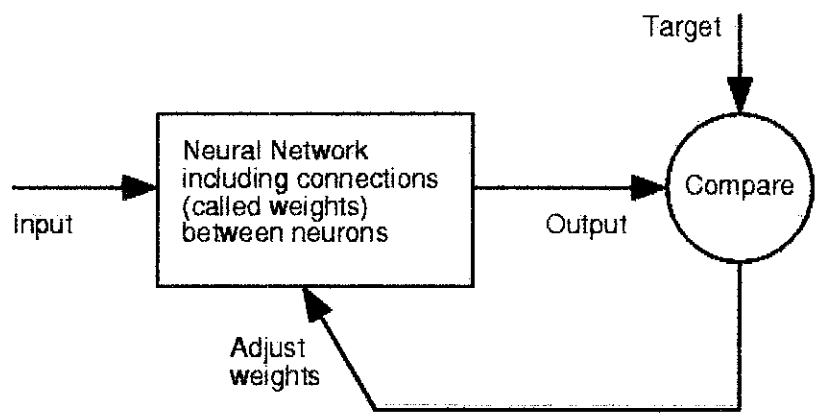


Figure 1: The Neural Network model

2.2.1 *Simple Neuron*

A simple neuron model with a single scalar input and no bias appears on the left below. The scalar input p is transmitted through a connection that multiplies its strength by the scalar weight w to form the product wp, again a scalar. Here, the weighted input wp is the only argument of the transfer function f, which then produces the scalar output a.

The neuron on the right has a scalar bias, b. The bias is being added to the product wp by the summing junction or as shifting the function f to the left by an amount b. The bias is much like a weight, except that it has a constant input of 1.

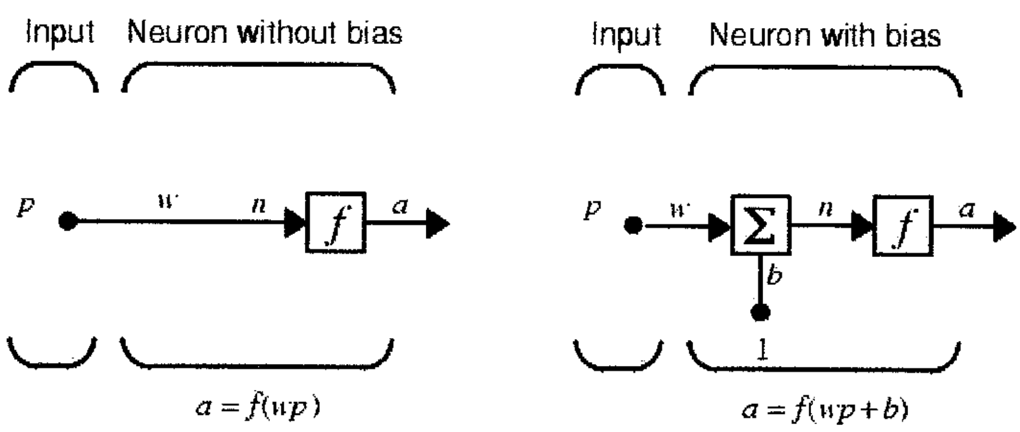


Figure 2: A simple neuron model

2.2.2 *Multilayer perceptron (MLP)*

MLP neural networks consist if units arranged in layers. Each layer is composed of nodes and each node connects to every node in subsequent layers. Each MLP is composed of a minimum of three layers consisting of an input layer, one or more hidden layers and an output layer. The input layer distributes the inputs to subsequent layers. Input nodes have linear activation functions and no thresholds. Each hidden unit node and each output node have thresholds associated with them in addition to the weights. The hidden unit nodes have nonlinear activation functions and the outputs have linear activation functions. Hence, each signal feeding into a node in a subsequent layer has the original input multiplied by a weight with a threshold added and then is passed through an activation function that may be linear or nonlinear (hidden units) [7].

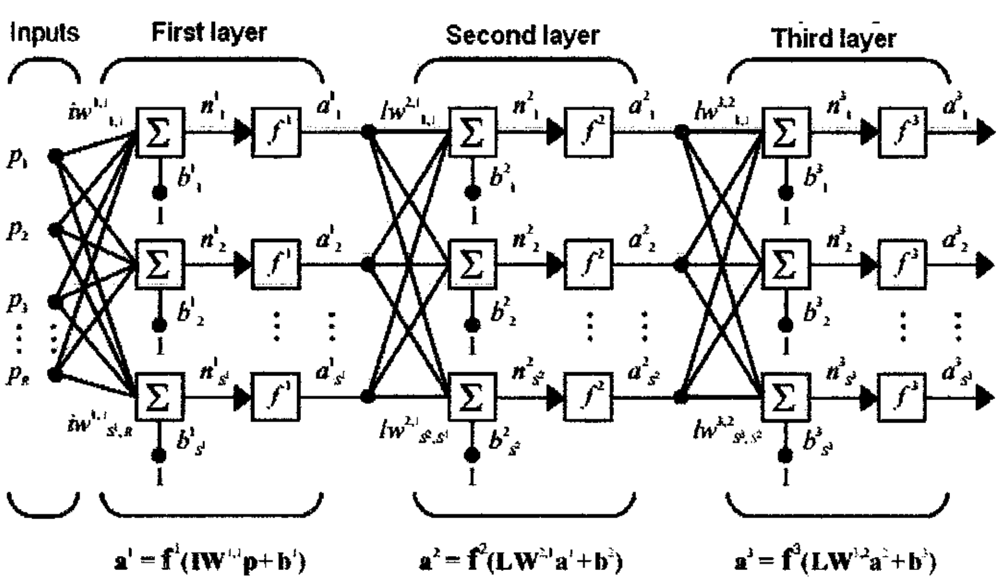


Figure 3: A three layer network

2.3 Energy Calculation

Gas volume is calculated from metered volume readings, pressure and temperature measurements and gas composition data. Based on ISO 6979 and AGA Report No.8, the energy consumption of sales gas is usually calculated using the equation below.

The hourly volume of gas in standard cubic meters per hour:

$$V_h = \sum_h \frac{V_g meas \times Pmeas \times Tbase \times Zbase}{Pbase \times Tmeas \times Zmeas} \qquad (1)$$

The hourly energy flow in GJ calculated per hour:

$$E_h = \left(\frac{V_h \times CV}{1000} \right) \qquad (2)$$

Where,

Eh = Energy consumption per hour (GJ)

Vh = Volume of gas per hour (Sm3)

CV = Carolific value (mJ/Sm3)

Vg(meas) = Measured gross volume (m3)

Pmeas = Measured pressure (kPa)

Pbase = Base pressure (kPa) (101.325 kPa)

Tmeas = Measured temperature (K)

Tbase = Base temperature (K) (288.15K)

Zmeas = Compressibility factor at Pmeas and Tmeas calculated by reference to AGA Report No.8

Zbase = Compressibility factor at Pbase and Tbase calculated by reference to AGA Report No.8

CHAPTER 3
METHODOLOGY

3.1 Procedure Identification

The activities for the project are summarized as the flow chart shown below.

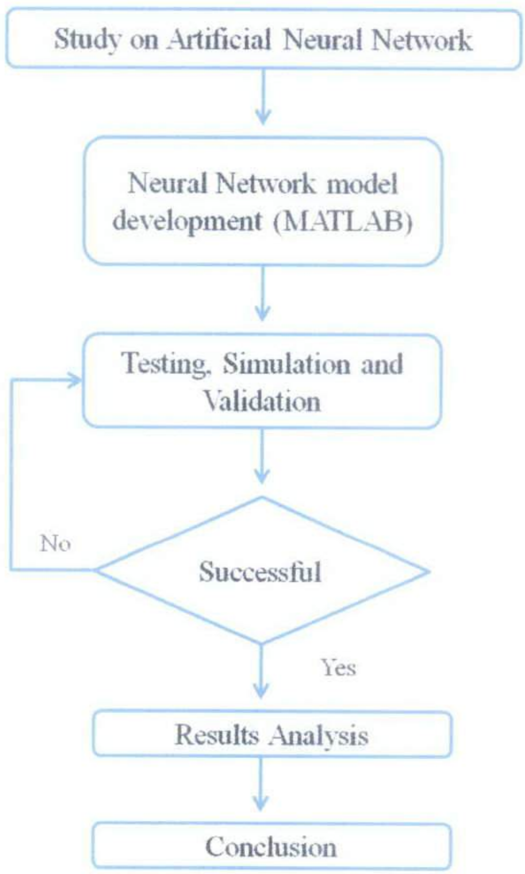


Figure 4: Project Activities Flow Chart

3.2 Project Activities

In the beginning of the project milestone, research had been done on several resources from books, technical papers and the internet. For the first step, gathering information needs to be done on the neural network and its architecture to acquire knowledge and understanding on the subject.

After all the studies had been done, the next phase is on the neural network model development. For this project, a neural network model is developed using MATLAB. This is where further research and studies is done about MATLAB because during this stage, the knowledge of MATLAB software is a requirement.

Then, the testing and validation work is done using simulation in MATLAB. This is where the model is tested until the desired results are achieved. The testing is done using trial and error method in order to get the best results. For a detailed project timeline, the Gantt chart for first and second semester is included in APPENDIX B and APPENDIX C.

3.3 Tools Required

For this project, Modelling and Simulation process for the design is done using MATLAB software. MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numeric computation. Using the MATLAB, technical computing problems can be solved faster than with traditional programming languages, such as C, C++, and Fortran. MATLAB is used in a wide range of applications, including signal and image processing, communications, control design, test and measurement, financial modeling and analysis, and computational biology.

Matlab is an extremely useful tool during the development and testing of a wide variety of applications. With built in ready-to-use functions that have been optimized for fast execution, and easy access to toolboxes and user generated contributions, it is possible to quickly implement and test various approaches before committing to a single one during the research and development process. In addition, if used properly, Matlab's graphical user interface (GUI) and display functions can help visualize data without spending hours coding in more complex languages and still retain the complexity provided by these alternatives [8].

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Data Gathering and Analysis

The data used for the development of neural network model is the actual historical data taken from the metering system flow computer (FC) in Transmission Operation Division (TOD), PETRONAS Gas Berhad (PGB), Gurun. The data consists of the actual energy data obtained from FC and value of input data from all the measuring equipments. There are five inputs which are Gross volume (Vg), Pressure (P), Temperature (T), Carolific value (CV) and Specific gravity (sg). The output is Energy (E).

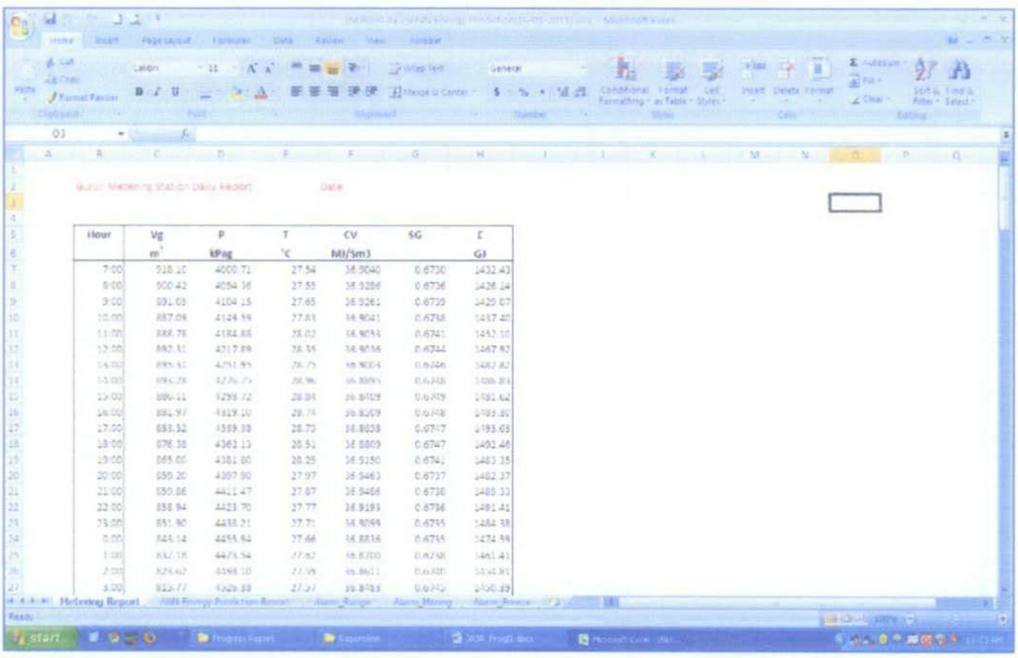


Figure 5: The actual data from Gurun Metering Station Daily Report

4.2 Experimentation / Modelling

4.2.1 MATLAB Algorithm

For this project, the neural network model is developed using MATLAB coding. The source code can be referred at APPENDIX A. For this model, it is a two layer-feed-forward neural network model trained with Bayesian Regulation (BR). This algorithm updates the weight and bias values according to the Levenberg-Marquardt (LM) optimisation and minimises a linear combination of squared errors and weights, and then determines the correct combination so as to produce a well generalised network. The BR takes place within the LM and requires more training and memory than the LM [9].

The network learns by applying a back-propagation algorithm which compares the neural network simulated output values to the actual values and calculates a prediction error. The error is then backpropagated through the network and weights are adjusted as the network attempts to decrease the prediction error by optimizing the weights that contribute most to the error [10].

Other than that, the network size is determined by setting the number of hidden neurons. The number of input nodes is a very important factor in neural network analysis of a time series since it corresponds to the number of past lagged observations related to future values. However, neural networks with one input node are too simple to capture the complex relationships between input and output, and it is rarely seen in the literatures that the number of input nodes is more than nine. Furthermore, too many nodes in the hidden layer produce a network that memorizes the input data and lacks the ability to generalize [11].

As for data division, 50 percent of the data for this neural network model is used for validation and 50 percent is used for training data. It is a common practice to divide the data into two sub-sets which are a training set and an independent validation set. Once the training (optimisation) phase has been completed, the performance of the trained network has to be validated on an independent data set which is the validation data [12].

The performance of the prediction model is evaluated based on the root of mean squared error (RMSE). The lower the RMSE value, the better prediction model developed.

$$RMSE = \sqrt{\frac{\sum_t \left(y_t - \hat{y}_t \right)^2}{T}} \qquad (3)$$

Where y_t is the actual value; $\hat{y}_t$ is the predicted value; T is the number of the predictions.

By using trial and error method, the network is simulated many times and the number of hidden neurons is set to be nine because it produces the lowest RMSE for validation data with 23 epochs. The results are as shown in Table 1.

Table 1: The number of neurons with the resulting RMSE values

No of Neurons	RMSE (Training data)	RMSE (Validation data)	No of Epochs
1	49.7645	46.38	25
2	50.2151	46.3103	14
3	14.0942	9.7105	74
4	13.9587	3.128	100
5	13.7842	8.7131	70
6	14.355	1.9368	54
7	14.3076	4.1397	20
8	13.0718	8.3255	58
9	14.2379	1.7692	23
10	14.4161	2.2975	60
11	14.2296	13.9916	30
12	14.4926	4.1523	22
13	14.4449	2.0599	53
14	14.2465	2.621	52
15	49.6213	45.6593	25

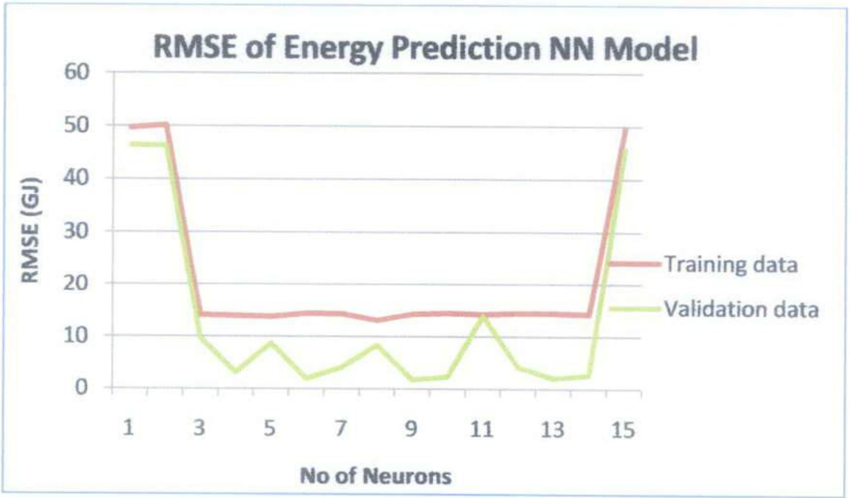


Figure 6: The validation and training RMSE trends

The simulated results are shown as Figure 7 below. There are four different graphs which are the output of Neural Network (NN) model for energy for validation data, output for training data, error between actual energy and predicted energy for validation data as well as error between actual energy and predicted energy for training data.

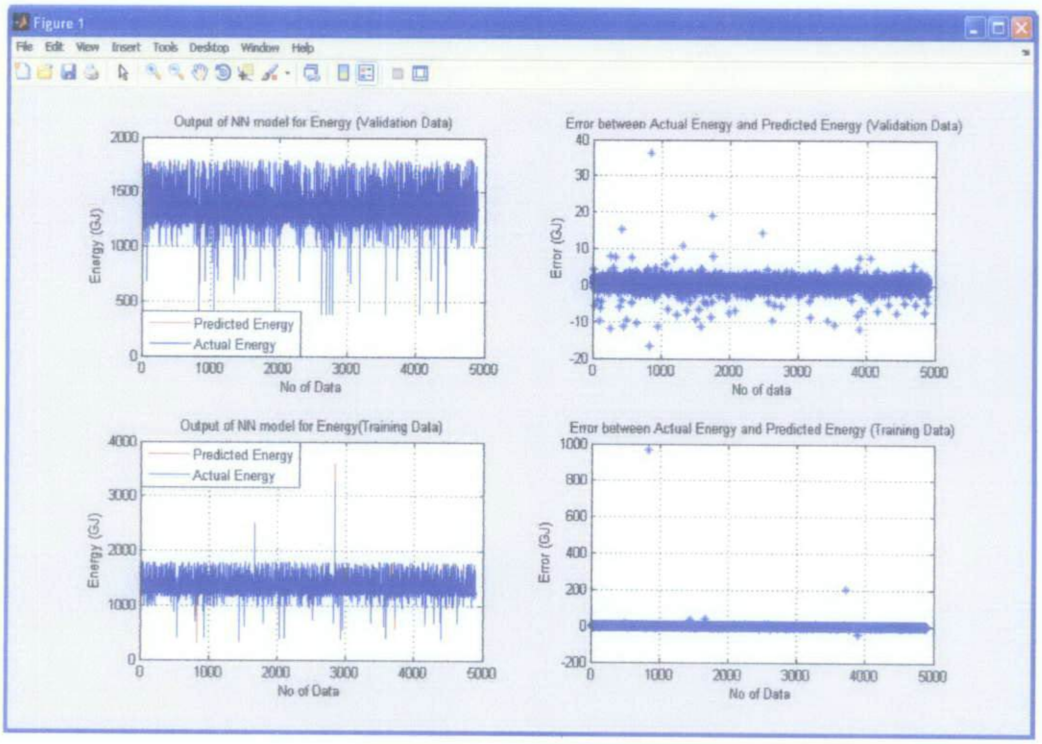


Figure 7: The output of NN model

It is clearly shown that the predicted and actual energy has similar characteristics and the error between them is close to zero value. The detailed error analysis can be referred to the Figure 8 below.

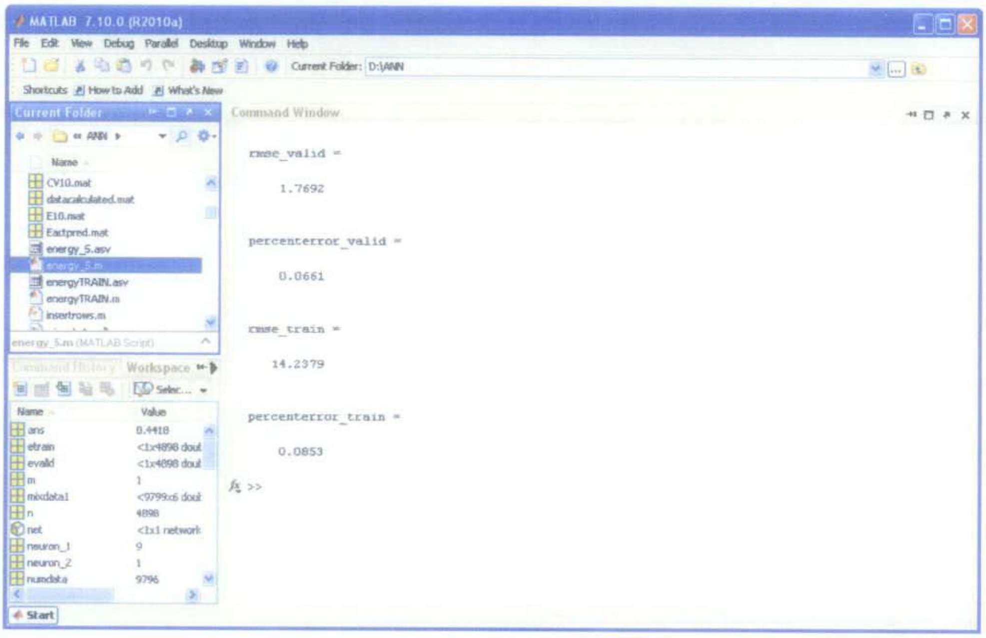


Figure 8: The error analysis

4.2.2 Neural Network Energy Predictor

The Neural Network Energy Predictor is a system used to predict the energy distributed to the customer. There are five inputs which are the gross volume (V_g), temperature (T), pressure (P), carolific value (CV) and specific gravity (sg). Then, the output is the energy (E).

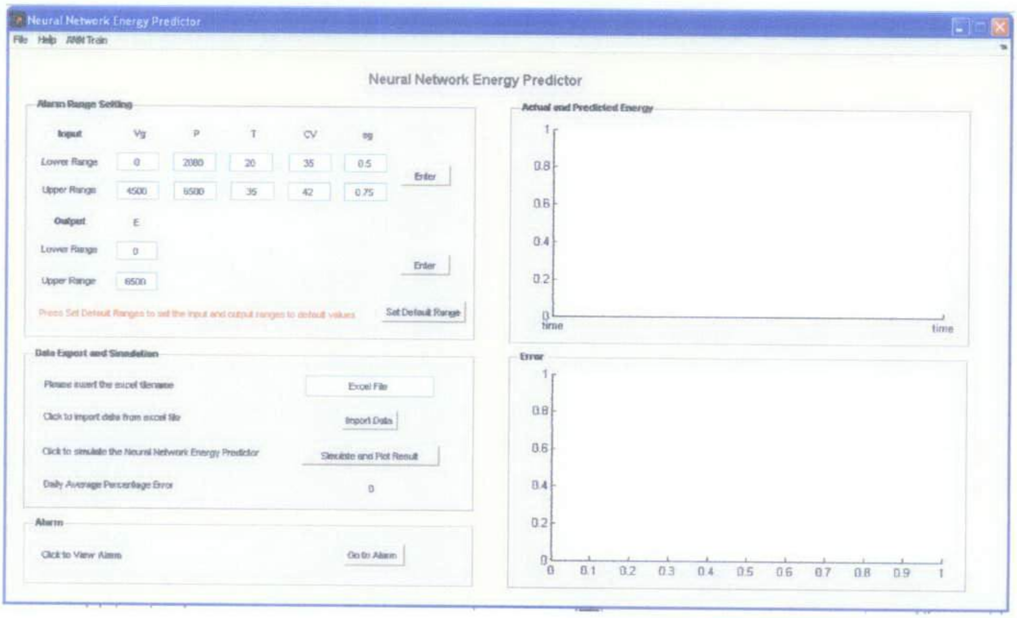
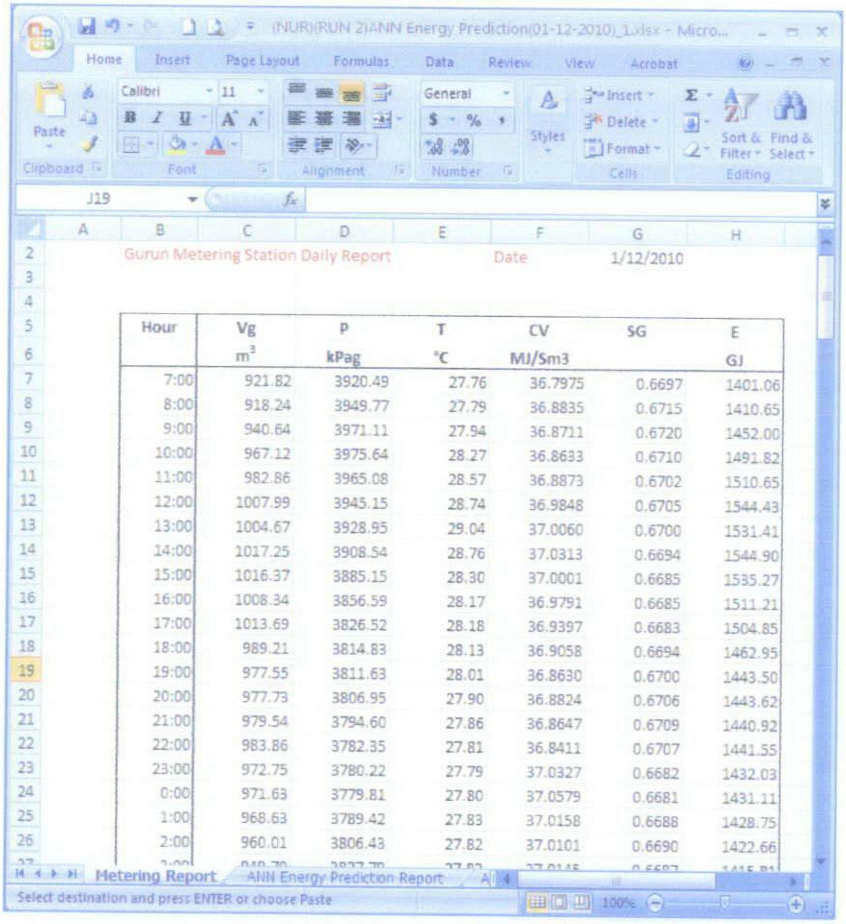


Figure 9: The Neural Network Energy Predictor

The Neural Network Energy Predictor displays the actual and predicted energy and also the percentage error between them.

Using The Neural Network Energy Predictor, the data is exported by copying the filename of an excel file containing real data from the Gurun metering system. The input data consists of hourly gross volume, pressure, temperature, calorific value, and specific gravity. Figure 10 shows the data on 01/12/2010.



Gurun Metering Station Daily Report Date 1/12/2010

Hour	Vg m^3	P kPag	T °C	CV MJ/Sm3	SG	E GJ
7:00	921.82	3920.49	27.76	36.7975	0.6697	1401.06
8:00	918.24	3949.77	27.79	36.8835	0.6715	1410.65
9:00	940.64	3971.11	27.94	36.8711	0.6720	1452.00
10:00	967.12	3975.64	28.27	36.8633	0.6710	1491.82
11:00	982.86	3965.08	28.57	36.8873	0.6702	1510.65
12:00	1007.99	3945.15	28.74	36.9848	0.6705	1544.43
13:00	1004.67	3928.95	29.04	37.0060	0.6700	1531.41
14:00	1017.25	3908.54	28.76	37.0313	0.6694	1544.90
15:00	1016.37	3885.15	28.30	37.0001	0.6685	1535.27
16:00	1008.34	3856.59	28.17	36.9791	0.6685	1511.21
17:00	1013.69	3826.52	28.18	36.9397	0.6683	1504.85
18:00	989.21	3814.83	28.13	36.9058	0.6694	1462.95
19:00	977.55	3811.63	28.01	36.8630	0.6700	1443.50
20:00	977.73	3806.95	27.90	36.8824	0.6706	1443.62
21:00	979.54	3794.60	27.86	36.8647	0.6709	1440.92
22:00	983.86	3782.35	27.81	36.8411	0.6707	1441.55
23:00	972.75	3780.22	27.79	37.0327	0.6682	1432.03
0:00	971.63	3779.81	27.80	37.0579	0.6681	1431.11
1:00	968.63	3789.42	27.83	37.0158	0.6688	1428.75
2:00	960.01	3806.43	27.82	37.0101	0.6690	1422.66

Figure 10: The data on 01/12/2010

Then, data is simulated and the graphs of actual and predicted energy and also the percentage error between them are displayed as shown in figure below. From Figure 11, it is shown that the daily average percentage error is 0.3395%.

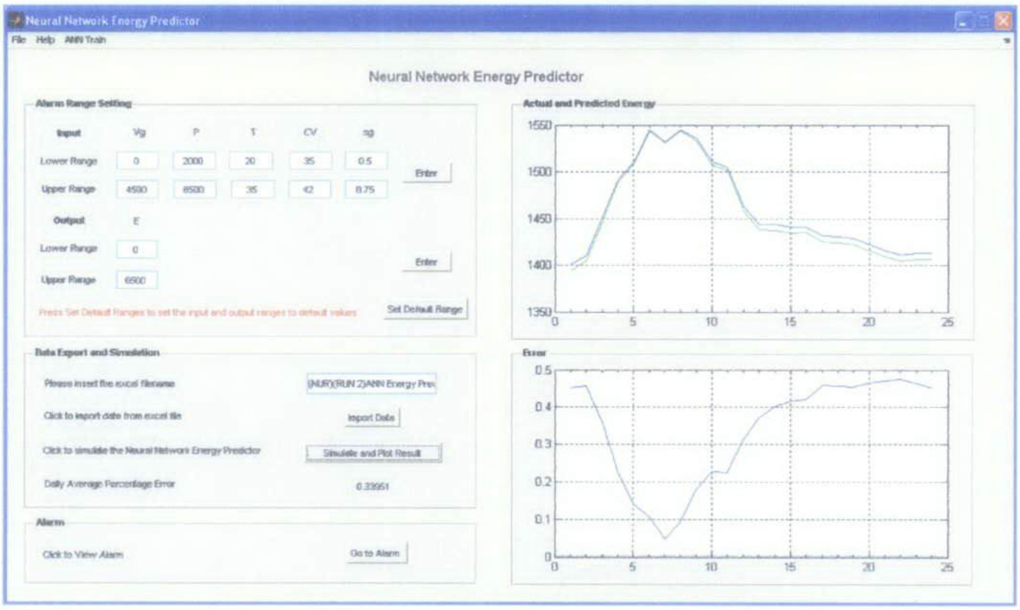


Figure 11: The simulated data on 01/12/2010.

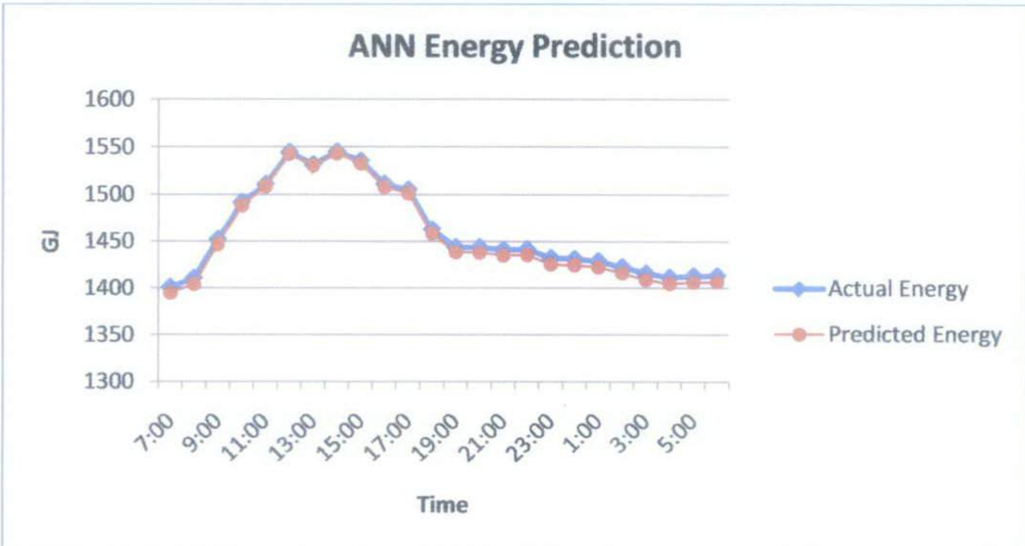


Figure 12: The graph of actual and predicted energy versus time

Figure 13: The graph of percentage error versus time

The simulated results show that the actual and predicted energy has similar pattern and all the percentage error is less than 0.5%. The simulation is continued by using data from other days. The Figure 14 below shows simulated data on 28/12/2010. The daily average percentage error is 0.5013%.

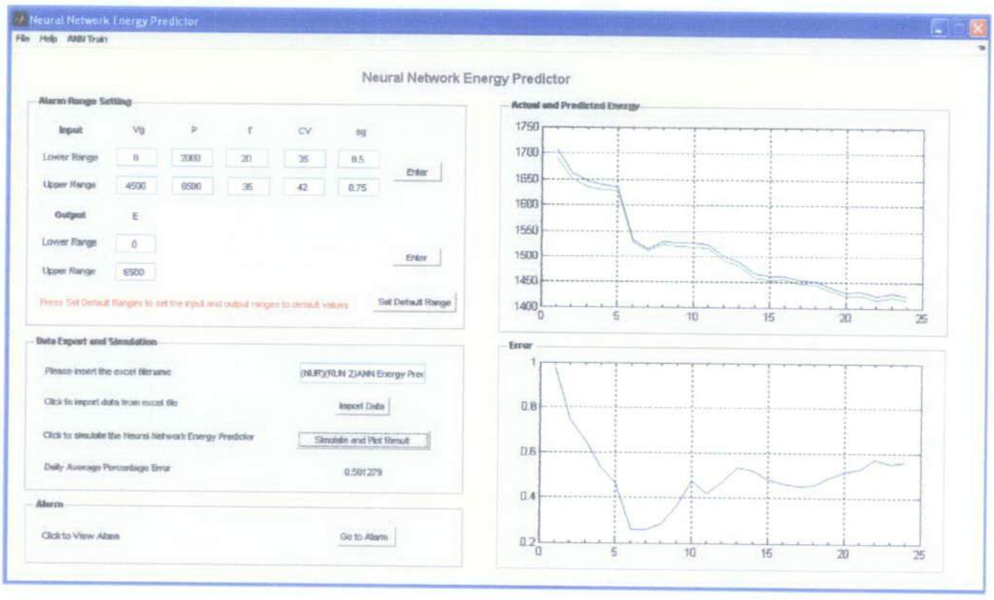


Figure 14: The simulated data on 28/12/2010

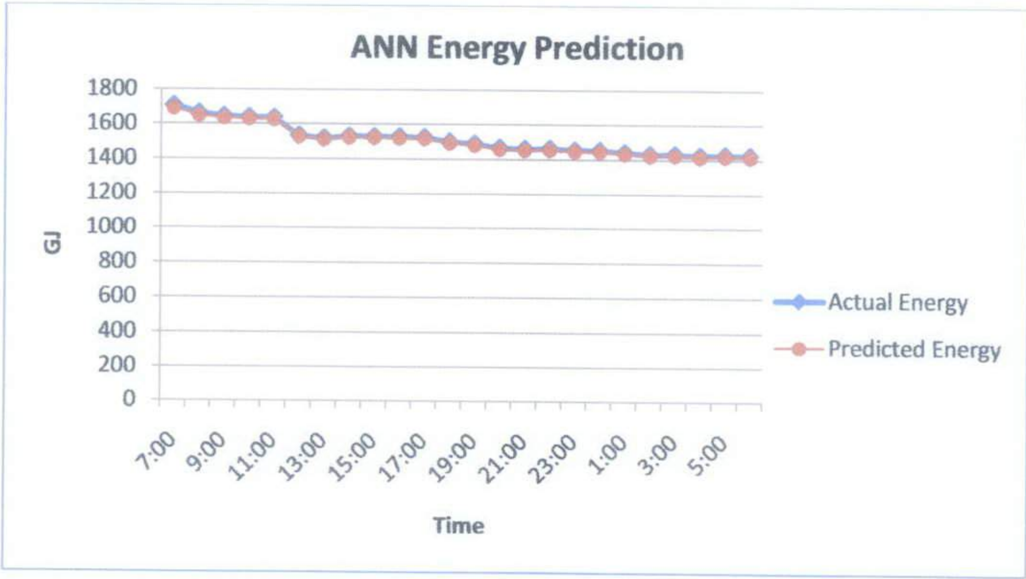


Figure 15: The graph of actual and predicted energy versus time

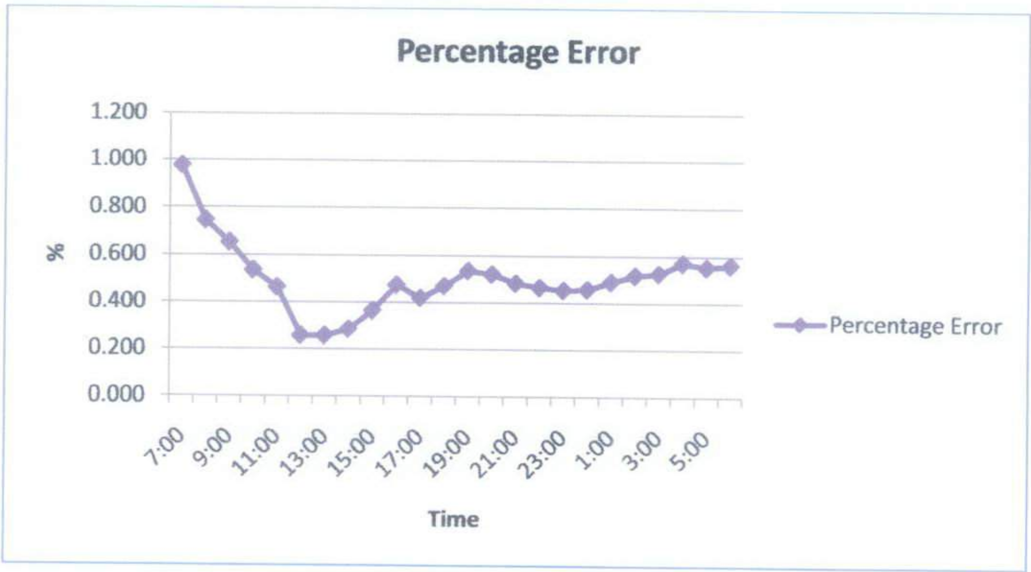


Figure 16: The graph of percentage error versus time

The simulated results show that the actual and predicted energy has similar pattern and all the percentage error is less than 1.0%.

The simulation is continued by using data from 16/01/2011 as shown in Figure 17 below. It is shown that the daily average percentage error is 0.3114%.

Figure 17: The simulated data on 16/01/2011

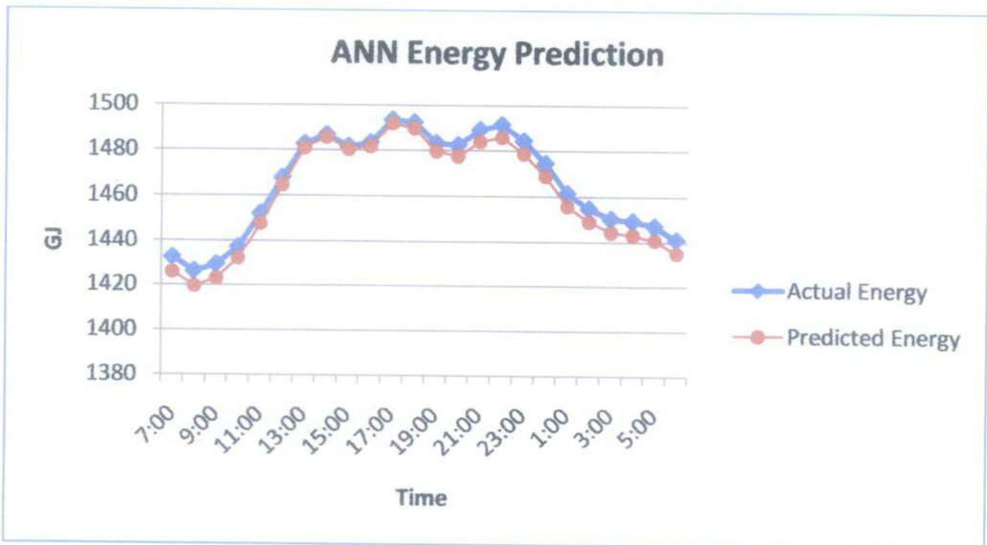


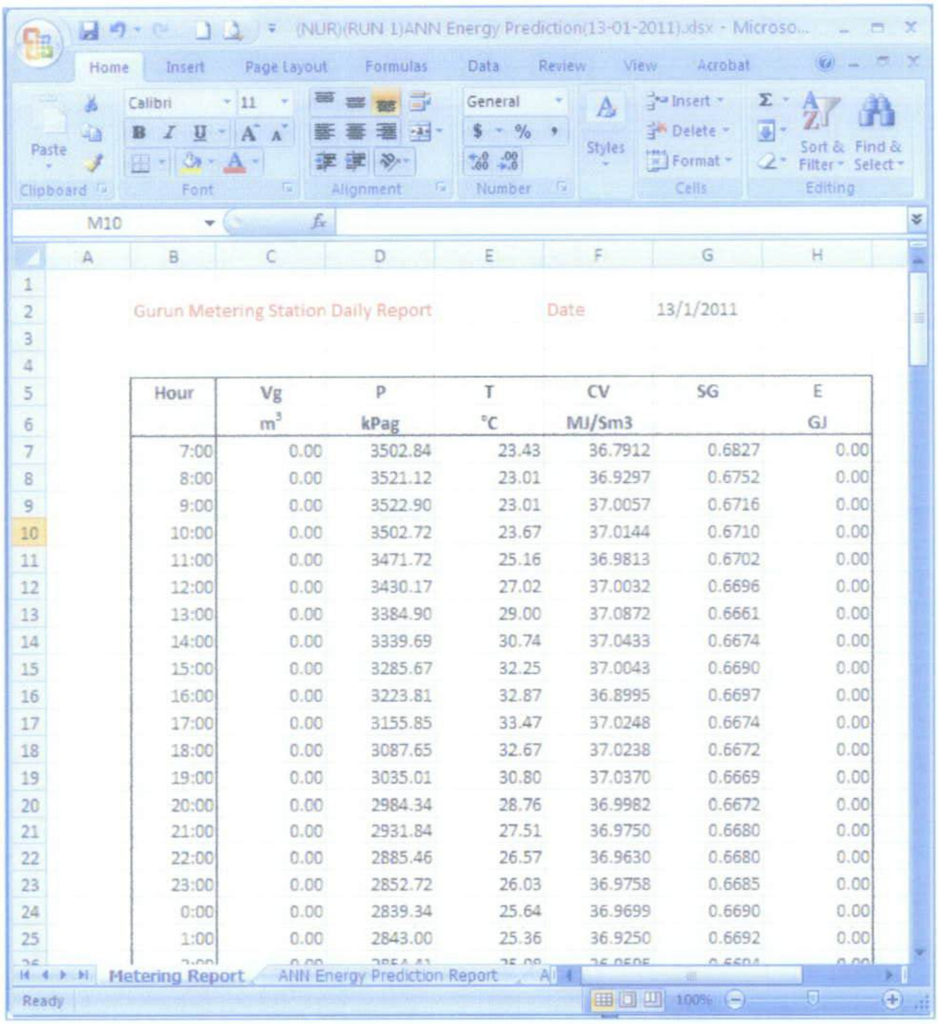
Figure 18: The graph of actual and predicted energy versus time

Figure 19: The graph of percentage error versus time

The simulated results show that the actual and predicted energy has similar pattern and all the percentage error is less than 0.5%.

4.2.2.1 Experimentation with missing data

In the data files from the Gurun metering station, there are some missing data especially the gross volume (V_g) data. Using The Neural Network Energy Predictor, it can also predict the energy even though there are missing data. The data on 13/01/2011 is as shown in Figure 20. The data for V_g is zero, thus the calculated energy, E is zero.


Gurun Metering Station Daily Report Date 13/1/2011

Hour	Vg	P	T	CV	SG	E
	m^3	kPag	°C	MJ/Sm3		GJ
7:00	0.00	3502.84	23.43	36.7912	0.6827	0.00
8:00	0.00	3521.12	23.01	36.9297	0.6752	0.00
9:00	0.00	3522.90	23.01	37.0057	0.6716	0.00
10:00	0.00	3502.72	23.67	37.0144	0.6710	0.00
11:00	0.00	3471.72	25.16	36.9813	0.6702	0.00
12:00	0.00	3430.17	27.02	37.0032	0.6696	0.00
13:00	0.00	3384.90	29.00	37.0872	0.6661	0.00
14:00	0.00	3339.69	30.74	37.0433	0.6674	0.00
15:00	0.00	3285.67	32.25	37.0043	0.6690	0.00
16:00	0.00	3223.81	32.87	36.8995	0.6697	0.00
17:00	0.00	3155.85	33.47	37.0248	0.6674	0.00
18:00	0.00	3087.65	32.67	37.0238	0.6672	0.00
19:00	0.00	3035.01	30.80	37.0370	0.6669	0.00
20:00	0.00	2984.34	28.76	36.9982	0.6672	0.00
21:00	0.00	2931.84	27.51	36.9750	0.6680	0.00
22:00	0.00	2885.46	26.57	36.9630	0.6680	0.00
23:00	0.00	2852.72	26.03	36.9758	0.6685	0.00
0:00	0.00	2839.34	25.64	36.9699	0.6690	0.00
1:00	0.00	2843.00	25.36	36.9250	0.6692	0.00

Figure 20: The data on 13/01/2011 with missing V_g

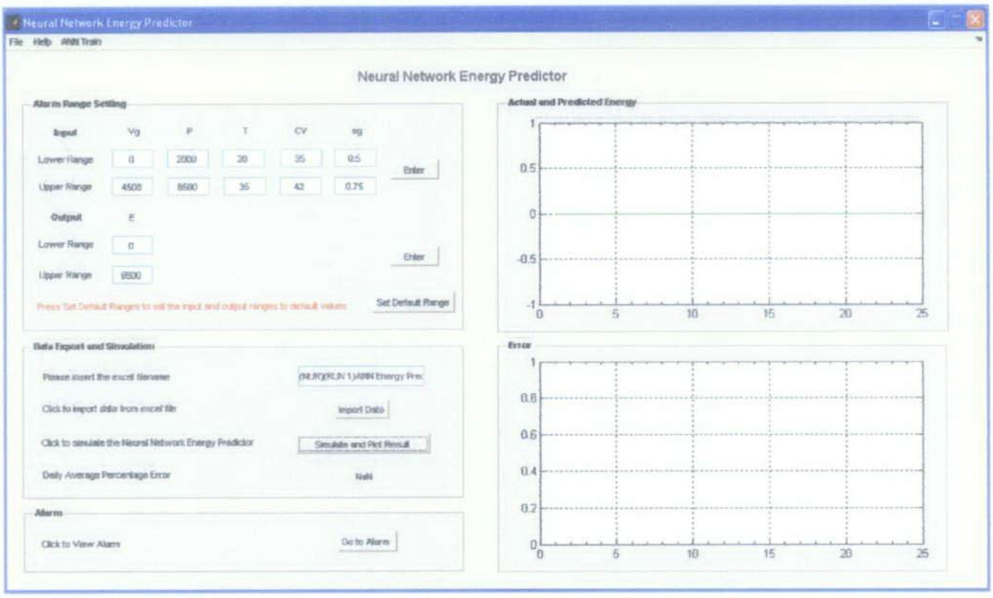
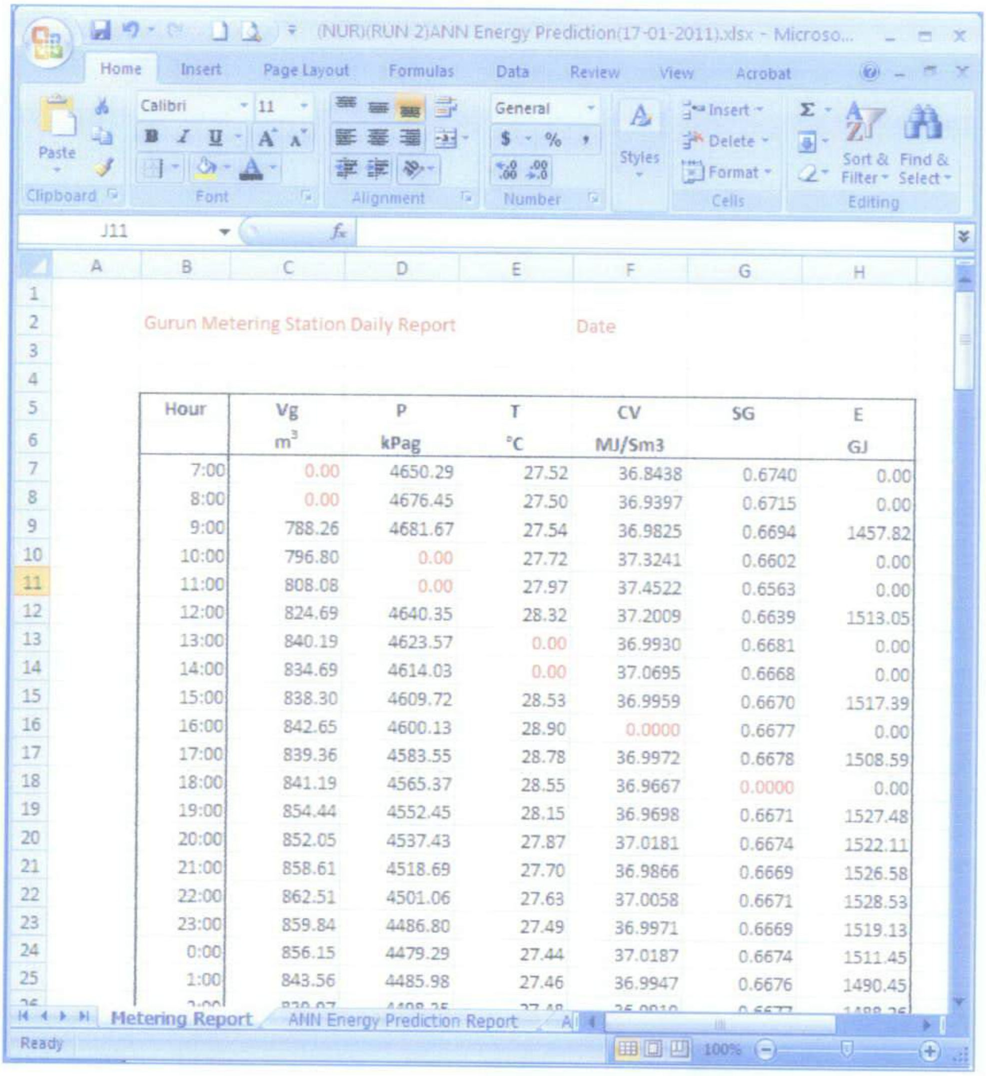


Figure 21: The simulated data on 13/01/2011

Figure 21 show that the Neural Network Energy Predictor can also predict the energy even though there are missing data. As the actual energy is zero, thus the predicted energy is also zero.

Other than that, the simulation is continued by using data from other days, whereby the other parameters such as temperature (T), pressure (P), carolific value (CV), specific gravity (sg) and even the energy (E) are manipulated to be zero to indicate data missing as shown in Figure 22 below.



Gurun Metering Station Daily Report Date

Hour	Vg m^3	P kPag	T °C	CV MJ/Sm3	SG	E GJ
7:00	0.00	4650.29	27.52	36.8438	0.6740	0.00
8:00	0.00	4676.45	27.50	36.9397	0.6715	0.00
9:00	788.26	4681.67	27.54	36.9825	0.6694	1457.82
10:00	796.80	0.00	27.72	37.3241	0.6602	0.00
11:00	808.08	0.00	27.97	37.4522	0.6563	0.00
12:00	824.69	4640.35	28.32	37.2009	0.6639	1513.05
13:00	840.19	4623.57	0.00	36.9930	0.6681	0.00
14:00	834.69	4614.03	0.00	37.0695	0.6668	0.00
15:00	838.30	4609.72	28.53	36.9959	0.6670	1517.39
16:00	842.65	4600.13	28.90	0.0000	0.6677	0.00
17:00	839.36	4583.55	28.78	36.9972	0.6678	1508.59
18:00	841.19	4565.37	28.55	36.9667	0.0000	0.00
19:00	854.44	4552.45	28.15	36.9698	0.6671	1527.48
20:00	852.05	4537.43	27.87	37.0181	0.6674	1522.11
21:00	858.61	4518.69	27.70	36.9866	0.6669	1526.58
22:00	862.51	4501.06	27.63	37.0058	0.6671	1528.53
23:00	859.84	4486.80	27.49	36.9971	0.6669	1519.13
0:00	856.15	4479.29	27.44	37.0187	0.6674	1511.45
1:00	843.56	4485.98	27.46	36.9947	0.6676	1490.45

Figure 22: The data with input parameters manipulated to be zero

The data is then exported into The Neural Network Energy Predictor and simulated. The results are as shown in Figure 23.

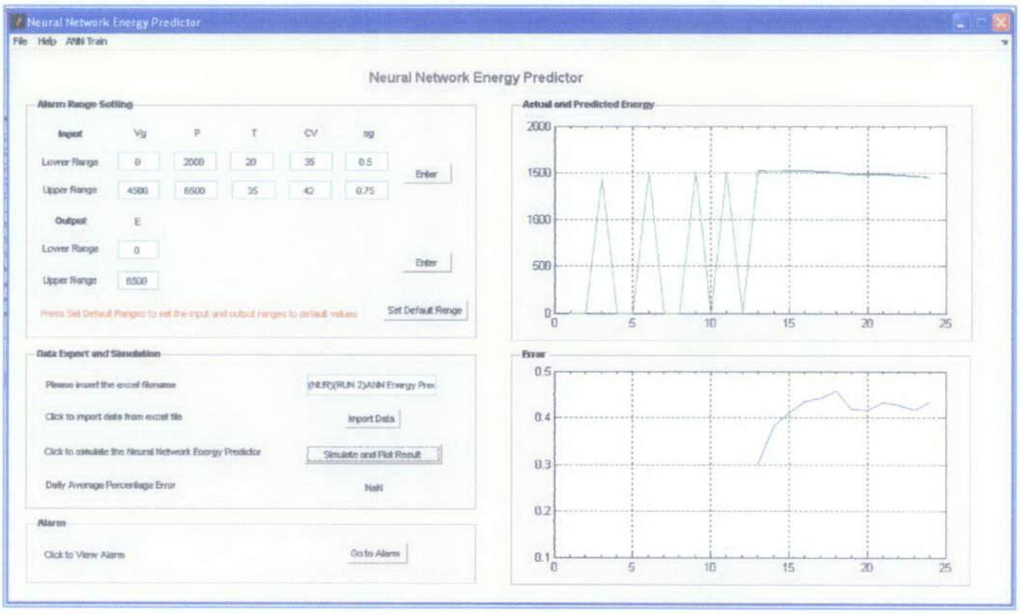


Figure 23: The simulated data on 17/01/2011

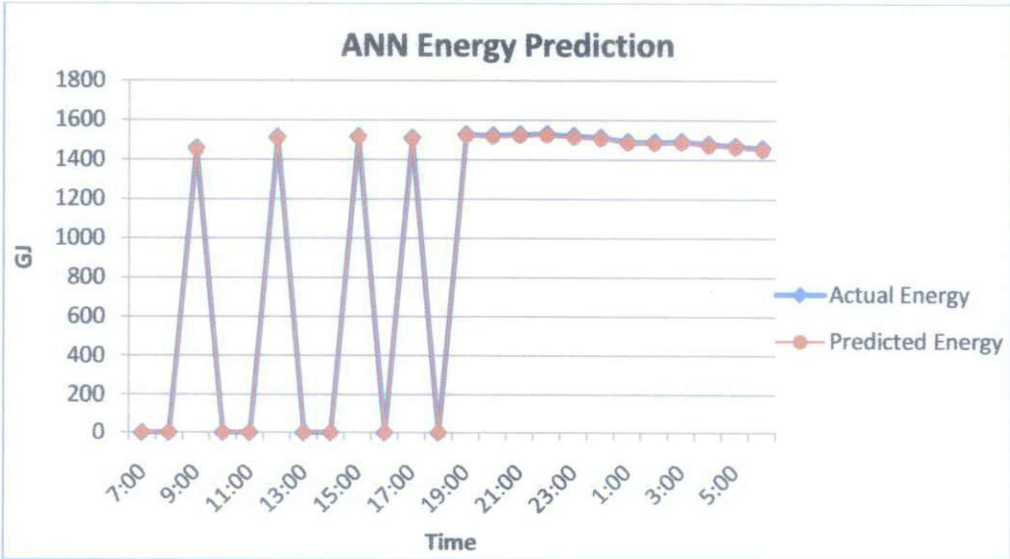
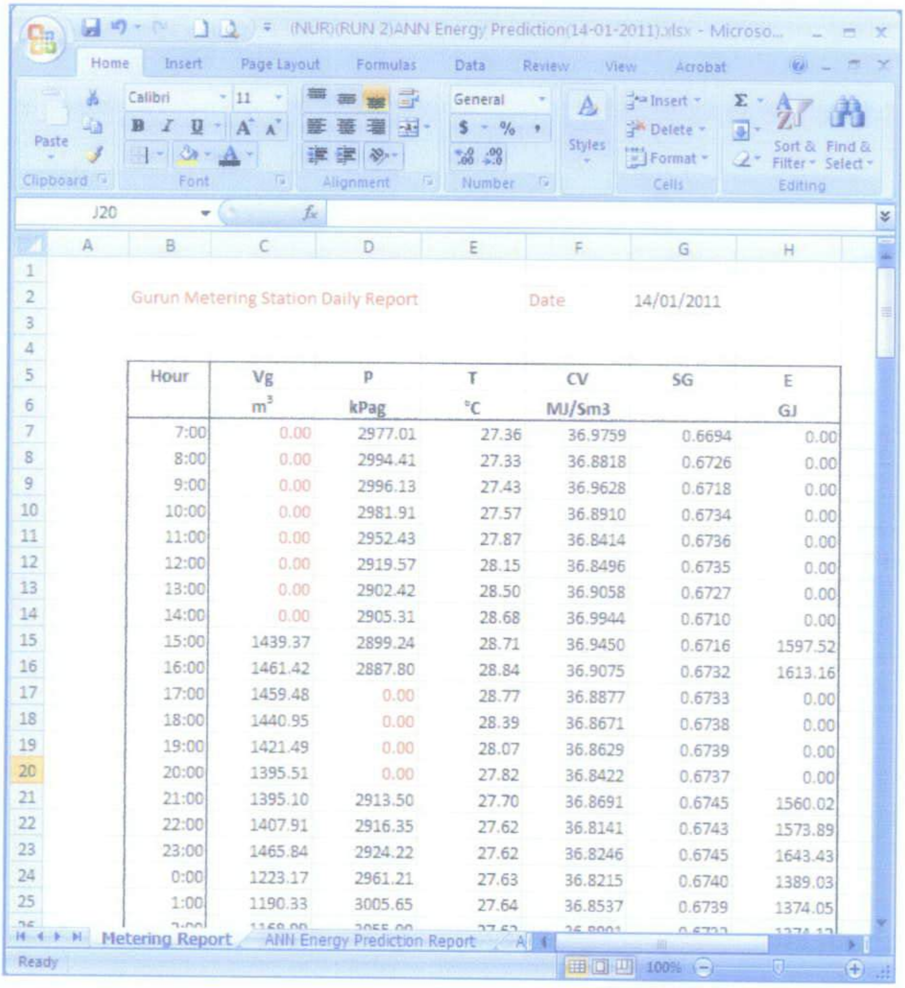


Figure 24: The graph of actual and predicted energy versus time

Figure 25: The graph of percentage error versus time

From Figure 24, it is clear that whenever there is data missing in any of the parameters, the energy predicted will be zero. Thus, the error between the actual and predicted energy will also be zero as displayed in Figure 25.

The simulation is continued by using data from 14/01/2011 as shown in Figure 26 below.



Gurun Metering Station Daily Report Date 14/01/2011

Hour	Vg m^3	P kPag	T °C	CV MJ/Sm3	SG	E GJ
7:00	0.00	2977.01	27.36	36.9759	0.6694	0.00
8:00	0.00	2994.41	27.33	36.8818	0.6726	0.00
9:00	0.00	2996.13	27.43	36.9628	0.6718	0.00
10:00	0.00	2981.91	27.57	36.8910	0.6734	0.00
11:00	0.00	2952.43	27.87	36.8414	0.6736	0.00
12:00	0.00	2919.57	28.15	36.8496	0.6735	0.00
13:00	0.00	2902.42	28.50	36.9058	0.6727	0.00
14:00	0.00	2905.31	28.68	36.9944	0.6710	0.00
15:00	1439.37	2899.24	28.71	36.9450	0.6716	1597.52
16:00	1461.42	2887.80	28.84	36.9075	0.6732	1613.16
17:00	1459.48	0.00	28.77	36.8877	0.6733	0.00
18:00	1440.95	0.00	28.39	36.8671	0.6738	0.00
19:00	1421.49	0.00	28.07	36.8629	0.6739	0.00
20:00	1395.51	0.00	27.82	36.8422	0.6737	0.00
21:00	1395.10	2913.50	27.70	36.8691	0.6745	1560.02
22:00	1407.91	2916.35	27.62	36.8141	0.6743	1573.89
23:00	1465.84	2924.22	27.62	36.8246	0.6745	1643.43
0:00	1223.17	2961.21	27.63	36.8215	0.6740	1389.03
1:00	1190.33	3005.65	27.64	36.8537	0.6739	1374.05

Figure 26: The data with input parameters manipulated to be zero

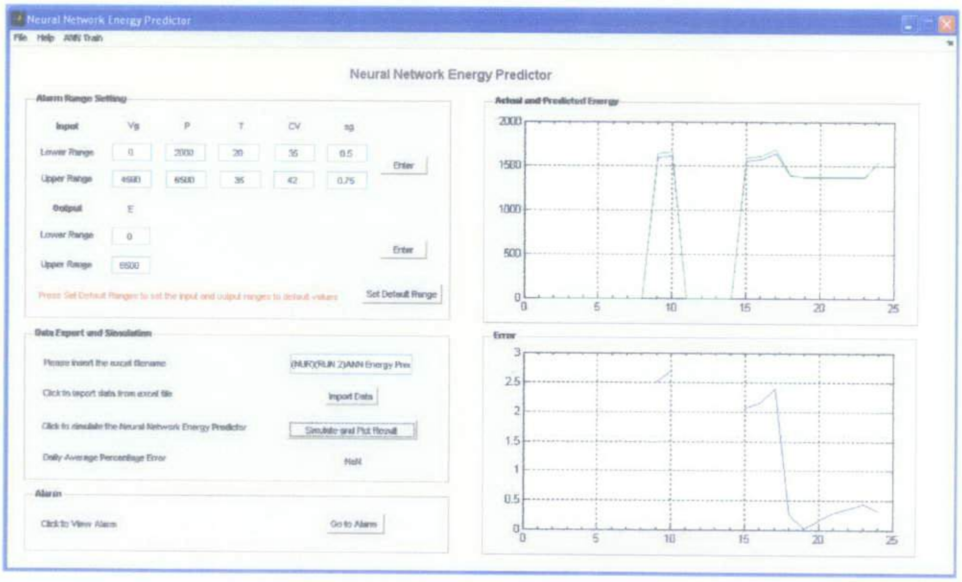


Figure 27: The simulated data on 14/01/2011

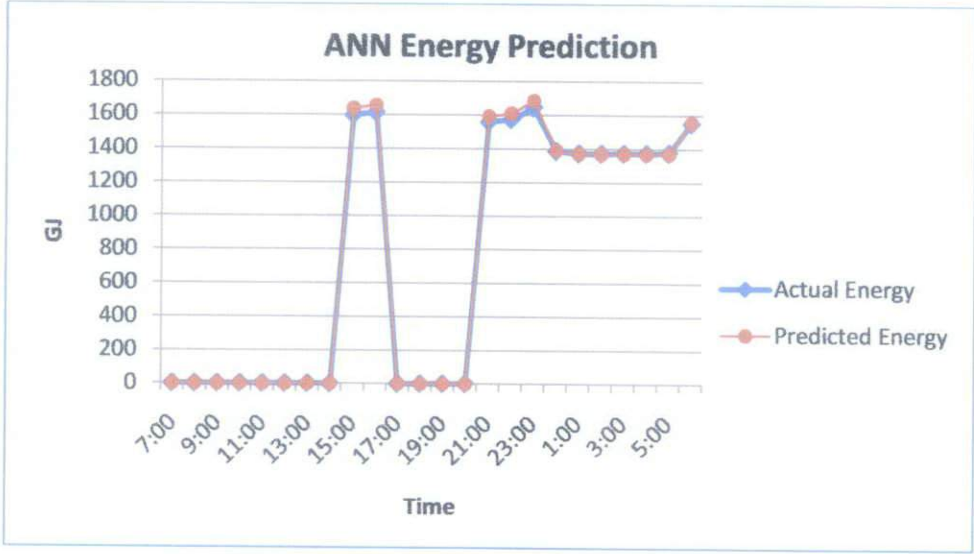


Figure 28: The graph of actual and predicted energy versus time

Figure 29: The graph of percentage error versus time

The simulated data shows that whenever there is data missing in any of the parameters, the energy predicted will be zero. Thus, the error between the actual and predicted energy will also be zero as displayed in figures above.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Developing a reliable neural network model for energy prediction is important to achieve accurate and precise forecast. The application of this model will assist the distributor in having a smooth gas transmission process and hence, bring more profits to the distributor.

Using MATLAB algorithm, a neural network model can be developed and has produced good prediction results by observing the model performance based on the root of mean squared error (RMSE). The lower the RMSE value, the better prediction model developed.

The Neural Network Energy Predictor is a reliable system that has been used in the Gurun Metering Station. This system is able to predict the energy distributed to the customer with error less than 1%.

However, the inconsistency of the error between the actual and predicted energy can be a problem. Thus, the neural network model needs to be trained with new sets of data but over training the network can also affect the results as the network is unable to properly generalize to a new data set.

5.2 Recommendations

There are a few recommendations for this project that can be implemented and applied so that the neural network model can be further improved. Firstly, as for now, the model used the data from only one metering station which is the Gurun metering station. As a recommendation, the neural network model can also be tested with many more testing data from other metering stations. Therefore, the robustness and reliability of the model can be increased.

Other than that, the capability of the system needs to be enhanced by improving it to be an online monitoring system. Currently, the existing system is an offline system which the data is inserted into the system manually. Hence, with an online metering system, the data can be automatically inserted and updated into the metering system.

Thus, for an online monitoring system, the neural network model can be developed to be an adaptive neural network. Therefore, much study and research needs to be done to explore the feasibility of using the adaptive neural network model.

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APPENDICES

APPENDIX A

ENERGY PREDICTION SOURCE CODE

```
%Clear workspace and command window
clc;

load mixdata1;

%load data from workspace
x = mixdata1(:,1:5)';
y = mixdata1(:,6)';

%-----------------------------------------------------------------%
%prepocess the input and output [-1,1]
%-----------------------------------------------------------------%
[x_i,x_s1] = mapminmax(x);   %INPUT training data
[y_i,y_s1] = mapminmax(y);   %OUTPUT training data
% [x_v1,x_s2] = mapminmax(x_v);   %INPUT validation data
% [y_v1,y_s2] = mapminmax(y_v);   %OUTPUT validation data
%maximum and minimum value of TRAINING data
t = minmax(x_i);

%-----------------------------------------------------------------%
%divide data into TRAINING and VALIDATION
%-----------------------------------------------------------------%
%get the number of input and number of data
numofdata=size(x,2); %number of data

% check if the number of data is even or odd value
if rem(numofdata,2)==0;
    numdata=numofdata-2;
else
    numdata=numofdata-3;
end

train_data = 0.5*numdata; %number of TRAINING data

validation_data =numdata-train_data; %number of VALIDATION data
numofvar = size(x,1); %number of input
numofout = size(y,1); %number of input

for m=1:numofvar
    for n=1:train_data
    x_t(m,n)=x(m,n);
    end
end

for m=1:numofvar
    for n=1:validation_data
    x_v(m,n)=x(m,n+train_data);
    end
end
```

```
for m=1:numofout
    for n=1:train_data
    y_t(m,n)=y(m,n);
    end
end

for m=1:numofout
    for n=1:validation_data
    y_v(m,n)=y(m,n+train_data);
    end
end


%-----------------------------------------------------------------%
%prepocess the input and output [-1,1]
%-----------------------------------------------------------------%
x_t1 = mapminmax('apply',x_t,x_s1);  %prepare INPUT data for
training
y_t1 = mapminmax('apply',y_t,y_s1);  %prepare OUTPUT data for
training
x_v1 = mapminmax('apply',x_v,x_s1);  %prepare INPUT data for
validation
y_v1 = mapminmax('apply',y_v,y_s1);  %prepare OUTPUT data for
validation
%maximum and minimum value of TRAINING data
t1 = minmax(x_t1);


%-----------------------------------------------------------------%
%set network properties
%-----------------------------------------------------------------%
%number of neurons for layer 1 and layer 2
neuron_1 = 9; %number of neurons for layer 1
neuron_2 = 1; %number of neurons for layer 2

%network and parameters
net=newff(x_i,y_i,neuron_1,{'tansig','purelin'},'trainbr');
net.trainParam.show = 50;
net.trainParam.lr = 0.1;
net.trainParam.epochs = 1000;
net.trainParam.goal = 0.001;
net=init(net);

%checking the weights and biases (make sure all are 0)
net.IW{1,1}; %weights of 1st layer
net.LW{2,1}; %weights of 2nd layer
net.b{1}; %bias of 1st layer
net.b{2}; %bias of 2nd layer
```

```
%--------------------------------------------------------------%
%train the network
%--------------------------------------------------------------%
[net,tr]=train(net,x_t1,y_t1);

%[net,y,e]=adapt(net,x_t1,y_t1);
%net.adaptParam.passes=100;



%--------------------------------------------------------------%
%simulate the network
%--------------------------------------------------------------%
%simulate the network with TRAINING data
xtest_t = mapminmax('apply',x_t,x_s1);  %prepare input data for
training

ytrain = sim(net,xtest_t);  %simulate the network
ytrain1 = mapminmax('reverse',ytrain,y_s1); %descale the output

%calculate the difference between the actual and predicted
temperature value
etrain=y_t-ytrain1;

%simulate the network with VALIDATION data
xtest_v = mapminmax('apply', x_v, x_s1);    %prepare input data
for training

yvalid=sim(net,xtest_v); %simulate the network
yvalid1 = mapminmax('reverse',yvalid,y_s1);%descale the output

%calculate the different between the actual and predicted
temperature value
evalid=y_v-yvalid1;


% %------------------------------------------------------------%
% %plot graph
% %------------------------------------------------------------%
% %plot the actual and predicted pH from VALIDATION data
subplot(2,2,1);
plot (yvalid1,'r');
hold on;
plot (y_v,'b');
xlabel('No of Data');
ylabel('Energy (GJ)');
title('Output of NN model for Energy (Validation Data)');
legend('Predicted Energy','Actual Energy');
grid on;
%

% %plot the difference between the actual and predicted pH from
VALIDATION data
subplot(2,2,2);
plot(evalid,'*');
```

```
xlabel('No of data');
ylabel('Error (GJ)');
title('Error between Actual Energy and Predicted Energy
(Validation Data)');
grid on;
%
% %plot the actual and predicted pH from TRAINING data
subplot(2,2,3);
plot (ytrain1,'r');
hold on;
plot (y_t,'b');
xlabel('No of Data');
ylabel('Energy (GJ)');
title('Output of NN model for Energy(Training Data)');
legend('Predicted Energy','Actual Energy');
grid on;

%plot the difference between the actual and predicted pH from
TRAINING data
subplot(2,2,4);
plot(etrain,'*');
xlabel('No of Data');
ylabel('Error (GJ)');
title('Error between Actual Energy and Predicted Energy (Training
Data)');
grid on;


%-----------------------------------------------------------------%
%error analysis
%-----------------------------------------------------------------%
%error analysis for the VALIDATION data
rmse_valid = sqrt(mse(evalid)) %mean square error
percenterror_valid = mean((abs(y_v-yvalid1)/y_v)*100)

%error analysis for the TRAINING data
rmse_train = sqrt(mse(etrain)) %mean square error
percenterror_train = mean((abs(y_t-ytrain1)/y_v)*100)
```

APPENDIX B

GANTT CHART: FIRST SEMESTER

No.	Detail/ Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Selection and Confirmation of Project Title								MID SEMESTER BREAK								STUDY WEEK		EXAM WEEK		
2	Gathering information on Neural Network																				
3	Submission of Preliminary Report																				
4	Study on Neural Network architecture and Matlab for Neural Network Model																				
5	Submission of Progress Report																				
6	Design modelling and simulation in MATLAB																				
7	Seminar																				
8	Finalize project work																				
9	Submission of Interim Draft Report																				
10	Submission of Interim Final Report																				
11	Oral Presentation																				

APPENDIX C

GANTT CHART: SECOND SEMESTER

No.	Detail/ Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Neural network model development and modification work																				
2	Submission of Progress Report							M													
								I													
3	Project work continues							D													
																S	E				
4	Testing and Validation work							S								T	X				
								E								U	A				
5	Pre-EDX							M								D	M				
								E								Y					
6	Finalize results and findings							S													
								T								W	W				
7	Submission of Draft Report							E								E	E				
								R								E	E				
8	Submission of Final Report and Technical paper.															K	K				
								B													
9	Oral Presentation							R													
								E													
								A													
								K													