FORECAST OF ELECTRICAL POWER DEMAND

LEE KHEN SHEN

A project report submitted in partial fulfilment
of the requirements for the award of
Master of Engineering in Electrical Engineering

Faculty of Engineering and Science
Universiti Tunku Abdul Rahman

May 2016

DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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Date   : **13 May 2016**

APPROVAL FOR SUBMISSION

I certify that this project report entitled **"FORECAST OF ELECTRICAL POWER DEMAND"** was prepared by **LEE KHEN SHEN** has met the required standard for submission in partial fulfilment of the requirements for the award of Master of Engineering in Electrical Engineering at Universiti Tunku Abdul Rahman.

Approved by,

Signature   : _____

Supervisor   : **Ir. Wee Sie Toon**

Date   : **13 May 2016**

SUBMISSION OF THESIS

It is hereby certified that **LEE KHEN SHEN (13UEM06681)** has completed this thesis entitled " **FORECAST OF ELECTRICAL POWER DEMAND** " under the supervision of **Ir. Wee Sie Toon** from the **Faculty of Engineering & Science.**

I understand that the University will upload softcopy of my thesis in pdf format into UTAR Institutional Repository, which may be made accessible to UTAR community and public.

Yours truly,

_____

(LEE KHEN SHEN)

Date : 13 May 2016

DEDICATION

Specially dedicated to

my best friends C.C Kok and C.H Teoh.

ACKNOWLEDGEMENTS

ABSTRACT

All electric utility companies employs some ways to manage their power generation capacity, for example using real-time SCADA management system. Through forecasting, utility company are able to plan ahead for the load requirements of the customers and meet the demands of consumers thus achieve efficiency in power generation. Accurate forecasting is needed due to these infrastructure incur high cost to build and maintain, also there is a lead time from around 1 to 3 years required for distribution lines and substations and around 3-7 years for power plants. Therefore forecasting helps the electric company to meet these demand by closely meeting the new required infrastructures efficiently.

Mix developments are on the rise in Kuala Lumpur, after the success stories of Mid Valley City and Publika. There are many new developments such as Paradigm, Pavilion and Sunway Velocity which follows the same concept of having residential (apartment/service residences) and commercial (shopping mall/offices) units built together and share the same podium floor. This paper attempt to forecast load demands for a community in a medium term basis, which will help developers and utility better understand the load requirements of such a development. Data taken will be analysed and used to forecast the load demands of the newly built development. From the forecasted data, the developer/utility (certainly) is able to have a better idea of the load profiles of a mix development power demands. The purpose is to be able to predict how the load demand will be like in the future. Thus, helping to anticipate future problems and getting ready the required infrastructures to cater to such demands. Which will be able to avoid costly interruptions and equipment failures. The deviation between the forecasted data and actual data should be low. Therefore is suitable to be used as a guide to help utility/developers in their judgement.

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LIST OF SYMBOLS / ABBREVIATIONS

LM	Levenberg-Marquardt
PE	Pencawang Elektrik
SSU	Stesen Suis Utama
PPU	Pencawang Pembahagian Utama
PMU	Pencawang Masuk Utama

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background

Forecasting is classified into short term, medium term and long term. Short term forecasting is for a period between hours to a week; medium term forecasting covers a period between a week to a year; long term forecasting covers anything that is more than a year (Feinberg & Genethliou 2005). Forecasting are used for a wide variety of decision making, it can be a simple task of estimating the time used for traveling from one place to another, it could be what is the weather like for the next few days to a month to plan for a trip overseas, it could be used to decide what a big company's direction is going to be for coming years taking into account the economic environment, market sentiments and company's resources. Basically, forecasting assist in planning activities to helps make enhance our lives. There have been many papers into forecasting models, mainly artificial neural network model, regression model and time series models.

The mix development which will be used for this paper, Empire Damansara consist of a Hotel tower, Residence tower, SOHO 1 & 2 towers, a 12 storey office block, 6 units of detached offices, a Multipurpose hall, Damansara Performing Arts Center (DPAC) & retail outlets and 5 and a half floors of carpark floors.

1.2   Project Aim

The focus of the paper is to forecast the electrical loads of a mix development community in order to help developer to plan the distribution system for a development and also a basis for utility companies to understand the load profile of such as development to prepare the necessary power demands required.

1.3   Project Objective

The objectives of this project are to:

1. To forecast the load of the new mix development with the use of the Levenberg-Marquardt algorithm in MATLAB functions and to compared to forecast of a saturated load development outputs.

1.4   Scope of the Project

The project consist of three main aspects to be achieved in order for the project to achieve its objectives:

1. To log the load data of the mix development for purpose of using in the forecasting in MATLAB.

2. To generate the MATLAB script for forecasting using Levenberg-Marquardt algorithm.

3. To optimized the MATLAB script for forecasting using Levenberg-Marquardt algorithm which is able to accurately forecast the load required.

CHAPTER 2

LITERATURE REVIEW

2.1   Forecasting Models

The initial idea of forecasting was that by observing past occurrences we're able to deduct and predict what might most likely happen in the near future. Forecasting consist of statistical models which have been experimented and used in last few decades mainly Artificial neural network, the regression model and time series models.

2.1.1   Artificial Neural Network Forecasting

In 1943, Warren McCulloch and Walter Pitts was the first to compute the neural network model into an electrical circuit by mimicking the brain's thinking process. Their research paved the way for further research in the area. Artificial neutral network (ANN) does not require prior data to be able to capture the relationships between the data and is well suited to solve problems which is hard to describe the relationship between data (Zhang et al. 1998). By passing information through these neurons or nodes, it will produce an output signal to other neurons or nodes and this forms the whole network. These process form a powerful computational network system that is able to process many different attributes and generalize patterns which have never been seen before. ANN is also able to learn from a small data sample and

come up and idea of how to predict or forecast future behaviours; Thirdly, ANN are able to estimate continuous functions to different sensitivity (Zhang et al. 1998). Lastly, ANN is a non-linear model, where it is able to recognize patterns without earlier information about the connections between data information, therefore making it a powerful tool compared to linear models. Therefore, neural network is outstanding compared to linear model in a way it is able to adapt to changes such as weekend or holidays and also drastic changes in weather.
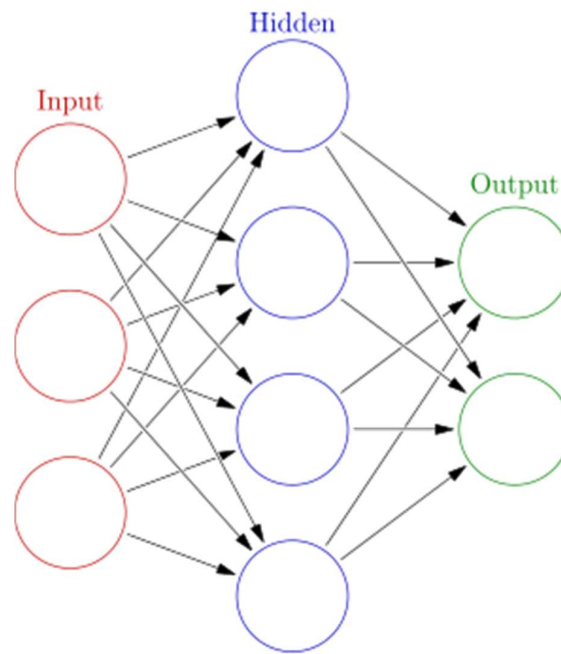
Figure 2.1   Simple ANN diagram.

In Figure 1.1, we can see the network's neurons or processing elements and each of it is a function given as $f^j(x)$. When input with data, each of it will produce a response $f^j(x) \in (1, 0)$. The function $f^j(x)$ is computed as below:-

$$f^j(x) = \Phi_{j(x)} \text{ when J is an input unit} \tag{1}$$

$$f^j(x) = s\left(\sum_{h \in \text{INPUTS (j)}} Wh, jf^h(x)\right) \tag{2}$$

$$s(z) = \frac{1}{1-e^{-z}} \tag{3}$$

By assuming there is a function $f^u(x)$ which is constant and equal to 1 for all x. And s (z) serves as a sigmoid function. If z >> 1 then s (z) is similar or equal 1 and if z << −1 then s (z) is similar or equal to 0. This permits every unit to be differentiated by comparing a weighted summation of inputs to an arbitrary unit. So every unit takes a weighted summations of its inputs and produces a yield if the data overcomes a certain limit. This is like what real neurons seem to do.

Independent of any connection to real neurons, neural systems are a vital model of computations. To calculate the disjunction, by comparing 10 times the total of the inputs to the threshold input 5. To process negations it suffices to think about negative ten times the info to the threshold input 5. These nodes will deliver values close to 0 and 1 regardless if the initial values are not exactly 0 or 1. Conjunction is achieved when both negations and disjunctions achieve similar results.

2.1.2   Regression model forecasting

Regression model is a statistical way to model for investigation of relationship between variables. For instances, certain changes of a variable will trigger the change the amount of increase of price upon inflation rate. Regression modelling is used in many different fields, such as economics, legal policy makers, even as evidence in court. Simple regression models as the name implies is simply measuring relationship of a property to a single attribute and coming up a hypothesis which in the real world does not seem realistic. For example the earnings of a individual is based on the number of years of education the person has received, or how a person and doesn't take into account what kind of expose he/she has experienced, which country in which field he/she has world in and so on. Simple scatter diagram is able to show how this theory is unrealistic by plotting based on the E which implies the higher the education vs I which implies the higher the income.
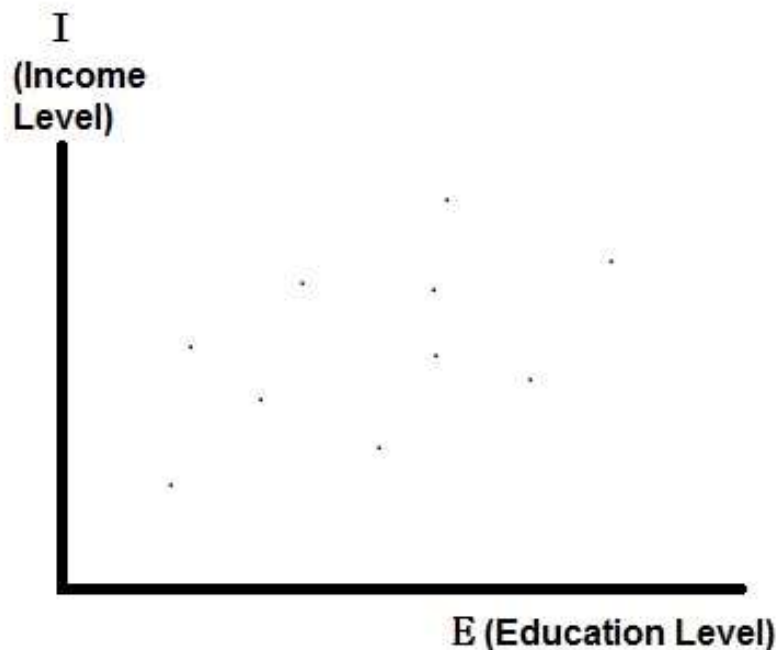
Figure 2.2   Scatter plot of Income vs Education

2.1.3   Time Series forecasting

Time series uses a set of data which is taken consecutively over a period of time. Time series modal as the name implies is a time dependent modal. It is usually dependant on a seasonal or weather trend. As it is dependent on these factors, when plotted against time or seasonal or weather, the time series model analysis is able to predict future value based by observing the past value. Therefore it is important to have data which is taken at a constant period of time. Time series forecasting is used for various types of fields such as economics and engineering. Draw backs of using time series is that it only takes consideration of the dependence of time and seasonal influences and it doesn't take into consideration other factors such as changes in economic conditions, political landscape, commodities market and etc. that might affect the forecasted data. Shown in Figure 2.3 is a yearly forecasted chart of peninsular Malaysia's power demand plotted over time, this is an example of how time series is being used to forecast future expected power demands.
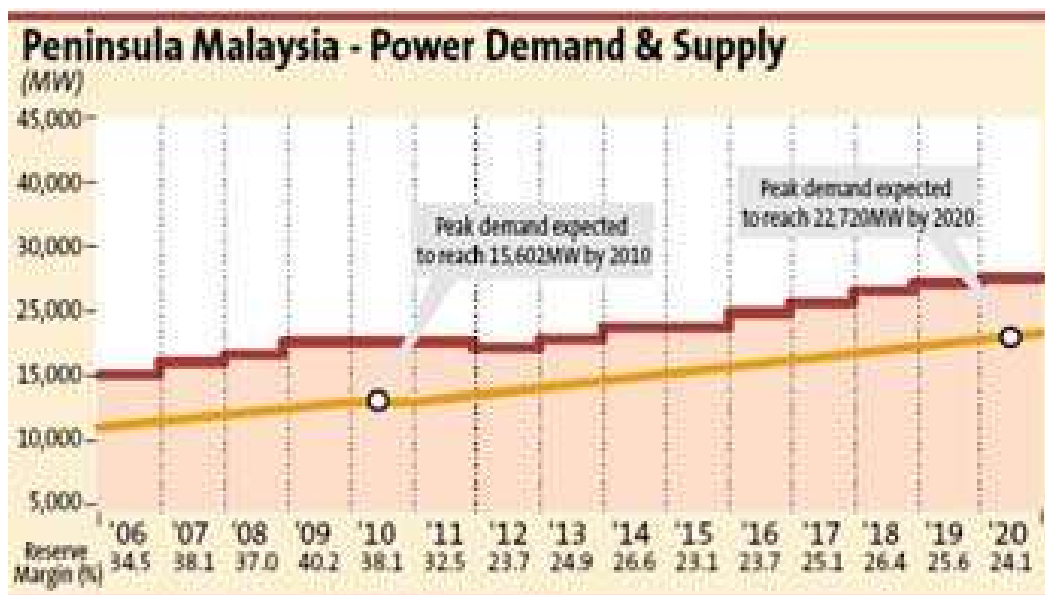
Figure 2.3   Power Demand projection for Peninsula Malaysia

2.1.4   Levenberg-Marquardt Method

The Levenberg-Marquardt method is a method which is used to locate the minimum of a function that is shown as a nonlinear least squares issues.

Least square problems emerges when:-

1.   The parameterized function is put into an arrangement of measured data by minimizing the summation of the squares of the deviations between the data and the function.

2.   The function is not linear to the parameters.

Nonlinear least squares method includes an iterative change to parameter values with the purpose to diminish the summation of the squares of the deviations between the function and the actual data taken.

The Levenberg-Marquardt method for smoothening data is a combination of two minimization techniques: the gradient descent method and the Gauss-Newton method. The gradient descent method is also known as the back propagation method.

The gradient descent method is done by lessening the summation of squared errors of the parameters in the steepest-descent way. In the Gauss-Newton method, the method is done by lessening the summations of the squared deviations and also assuming the least squared function is a quadratic function to find the base of the quadratic. The Levenberg-Marquardt method acts more like the gradient descent method when the parameters are a long way from their ideal values, and acts more like the Gauss-Newton method when the parameters are near their ideal values.

The Levenberg-Marquardt algorithm in the form of sum of squares function is given as follow:-

$$E = \frac{1}{2}\Sigma\, k(e_k)^2 = \frac{1}{2}\|e\|^2 \tag{3}$$

e_k is the error is a pattern

e is a vector with element e_k

When the differentials between the previous vector values and new vector values are not significant, the error vector can be expanded to 1st order using the Taylor series.

$$e(j + i) = e(j) + \frac{\partial e_k}{\partial w_i}(w(j + 1) - w(j)) \tag{4}$$

Substituting (4) into (3) we are able to show the error function as :-

$$E = \frac{1}{2}\left\| e(j) + \frac{\partial e_k}{\partial w_i}(w(j + 1) - w(j)) \right\|^2 \tag{5}$$

Subsequently by minimizing the error function with respect to the new vector:-

$$w(j + 1) = w(j) - (Z^T Z)^{-1} Z^T e(j) \tag{6}$$

Where, $(Z)_{ki} \equiv \dfrac{\partial e_k}{\partial w_i}$

The Hessian for the sum of square error function is

$$(H)_{ij} = \frac{\partial^2 E}{\partial w_i \partial w_j} = \Sigma \left[\left(\frac{\partial e_k}{\partial w_i} \right) \left(\frac{\partial e_k}{\partial w_i} \right) + \frac{e_k \partial^2 e_k}{\partial w_i \partial w_j} \right] \tag{7}$$

By assuming the second term is negligible the Hessian function can be written as:-

$$H = J^T J \tag{8}$$

To update the weights will require the use of inverse Hessian for nonlinear networks. The Hessian equation is based on first order derivatives with the weights which is possible to be captured by the backpropagations.

The Levenberg-Marquardt algorithm is able to minimize the error function while keeping the step size small. This enables the function to be validate the linear approximations. This modified error function is given by the equation:-

$$E = \frac{1}{2} \left\| e(j) + \left(\frac{\partial e_k}{\partial w_i} \right) (w(j+1) - w(j)) \right\|^2 + \lambda \| W(j+1) - W(j) \|^2 \tag{9}$$

Where, λ is the parameter that governs the step size.
Minimizing the error in w(j+1) gives the equations:-

$$w(j+1) = W(j) - (Z^T Z + \lambda I)^{-2} Z^T e(j)$$

With very large values of λ the equation leans towards gradient descent method, with very small values of λ the equation leans towards the Newton-Gauss method.

2.1.5   Deviations of forecasting data vs actual data

To compare the data generated by each forecasting model, there are few methods that are commonly used. These methods are shown as follow:-

1. Mean absolute error (MAE),
2. Mean absolute percentage error (MAPE),
3. Mean squared error (MSE) or Root mean squared error (RMSE).

Formula of mean absolute error or also known as mean absolute deviation is given as:-

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|$$

Where A_t is the actual value and F_t is the forecast value.

The formulae for mean absolute percentage error is given as:-

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \; x \; 100\%$$

Where A_t is the actual value and F_t is the forecast value.

And the formula for mean squared error is given as:-

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2$$

Where A_t is the actual value and F_t is the forecast value.

2.2   TNB Tariffs and Load Distribution Planning

The sole power distributer in Peninsular Malaysia is Tenaga Nasional Berhad (TNB). They operate all the distribution lines in the entire peninsular Malaysia, which includes HV lines, MV and lastly LV lines. Therefore they have a set of guidelines on new consumers applying for the electricity supply of each development. Depending on developer/consumers load demand requirements, a substation or substations are

required to be built to serve the new development. From the largest distribution substation, a Pencawang Masuk Utama (PMU) which is a 275/132/33kV substation, to Pencawang Pembahagian Utama (PPU) which is a 33/11kV substation. Stesen Suis Utama (SSU) which is either a 33kV or a 11kV intake switching station and lastly Pencawang Elektrik (PE) or 11kV/415V substation. The same load requirements requested by the developer will be used to enforce the "cas sambungan beban" or "connected load charges" where the charges are enforced in the Table 2.1 when the load does not meet or exceeds certain percentage.

Year	Maximum Demand load reference	Charged connected load if exceeded this value
1	No. M.D reference	N/A
2	50% of declared M.D	75% x 50% = 37.5% of declared M.D.
3	75% of declared M.D.	75% x 75% = 56.25% of declared M.D
4,5 & 6	100% of declared M.D.	100% x 75% = 75% of declared M.D

Table 1.1   TNB Connected Load Charge reference

Maximum demand charge is another charge imposed by TNB to discourage customers to limit the peak usage of power. The introduction of Peak and Off-peak tariffs was introduced to lower the peak power usage and encourages customers to use energy storage systems like cold water storage system for large buildings to utilize power during the night time. Maximum demand is defined by the highest electricity demand recorded by TNB electric meter during a 30-minute interval in a month. The amount charged to customer is based on the recorded MD in kW multiplied by the respective MD rate. For low voltage customers of all different categories the M.D charges do not apply. For other customers, the MD tariff for medium voltage customers are tariff C1 and C2(peak & off peak) is RM30.30/kW and RM45.10/kW respectively.

The calculation for maximum demand charges is as follow:-
Maximum Demand Charges = Maximum demand recorded x Tariff for maximum demand

2.3 Power distribution System

The incoming TNB power source for the Empire Damansara SSU (11kV intake) comes from the nearby PPU (33/11kV) most probably PPU Mutiara Damansara as shown in Figure 2.4.

Figure 2.4   PPU Mutiara Damansara which serves the surrounding area.

The TNB SSU of Empire Damansara has 2 incoming 11kV feeders and 2 outgoing 11kV feeders as shown in the schematic Figure 2.5. The TNB SSU feeder goes to the Substation no. 5. The mix development consist of 6 main substations which distributes to the different parts of the whole development which is served via a 11kV ring / loop distribution which starts at substation no. 5. Each substations serve the different areas as follow:-

1. Substation no. 1 serves the the 5 storey basement carpark and detached offices.

2. Substation no. 2 serves the 12 storey Uzma office block and Jewel multipurpose building

3. Substation no. 3 serves the Studio Residential tower

4. Substation no. 4 serves the Qliq Hotel tower and facilities.

5. Substation no. 5 serves the SOHO 2 Residential tower

6. Substation no. 6 serves the SOHO 1 Residential tower and LG1, Ground and Level 1 retail units.
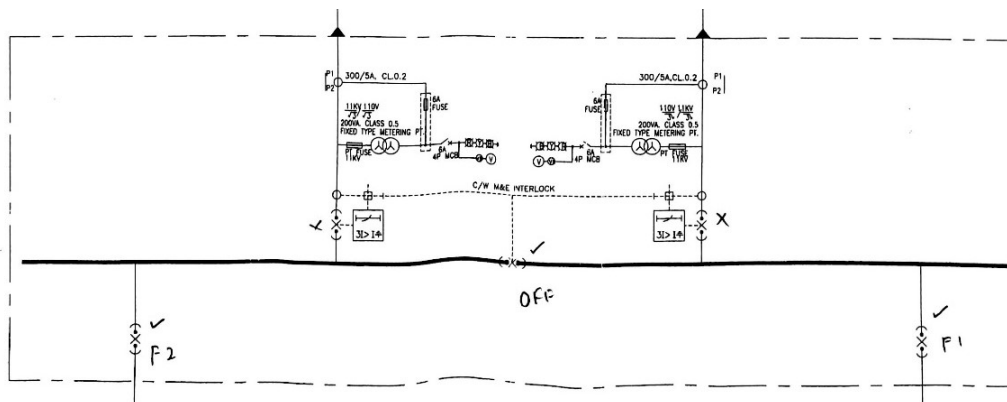
Figure 2.5   TNB 11kV SSU Substation Schematic Diagram.

Substation no.5 as shown in Figure 2.6 schematic, consist of 6 nos. of 11kV switchgears which consist of 5 incoming feeders and 2 outgoing feeders. 2 of the incoming 11kV switchgear are the feeders from the TNB SSU switchgear panel. The remaining 2 nos. of incoming feeders are connected to Substation No.6 and Substation No.2 respectively. The outgoing feeders as shown in Figure 2.7 serves the 2 nos. of 11kV/415V transformers namely TX 5-1 & TX 5-2 as shown in Figure 2.8, which are both 1600kVA transformers. There are 2 electric meters as shown in Figure 2.27 monitoring the consumption at both the incomings of low voltage switchboard (MSB No.5) as shown in Figure 2.6 installed with the current transformers.

Figure 2.6   Substation No.5 Switchgear panel schematic diagram

Figure 2.7   Switchgear panels for Substation No.5

Figure 2.8   Transformers TX 5-1 & TX 5-2.

Substation no.1 as shown in Figure 2.9 schematic, consist of 5 nos. of 11kV switchgears which consist of 2 incoming feeders and 3 outgoing feeders. The 2 nos. of incoming feeders as shown in Figure 2.10 are connected to Substation No.2 and Substation No.3 respectively. The outgoing feeders serves the 3 nos. of 11kV/415V transformers namely TX 1-1, TX 1-2, TX 1-3 as shown in Figure 2.22 are all 2000kVA transformers. There are electric meters as shown in the Figure 2.21 monitoring the consumptions at three of the incomings of low voltage switchboard (MSB No.1) installed with the current transformers.

Figure 2.9   Substation No.1 Switchgear panel schematic diagram

Figure 2.10   Switchgear panels for Substation No.1

Figure 2.11   Transformers TX 1-1, TX 1-2 & TX 1-3.

Substation no.2 as shown in Figure 2.12 schematic, consist of 4 nos. of 11kV switchgears which consist of 2 incoming feeders and 2 outgoing feeders. The 2 nos. of incoming feeders are connected to Substation No.6 and Substation No.1 respectively The outgoing feeders serves the 2 nos. of 11kV/415V transformers namely TX 2-1 & TX 2-2 as shown in Figure 2.13 which are both rated at 1600kVA. There are two electric meters as shown in the Figure 2.23 & 2.24 monitoring the consumptions at both the incomings of low voltage switchboard (MSB No.2) installed with the current transformers.

Figure 2.12   Substation No.2 Switchgear panel schematic diagram

Figure 2.13   Switchgear panels for Substation No.2 and TX2-1 & TX 2-2.

Substation no.3 as shown in the Figure 2.14 schematic, consist of 4 nos. of 11kV switchgears which consist of 2 incoming feeders and 2 outgoing feeders. The 2 nos. of incoming feeders are connected to Substation No.1 and Substation No.4 respectively The outgoing feeders as shown in Figure 2.15 serves the 2 nos. of 11kV/415V transformers namely TX 3-1 & TX 3-2 as shown in Figure 2.16 which are both rated at 1600kVA. There are electric meters as shown in the Figure 2.25 & 2.26 monitoring the consumptions at both the incomings of LV switchboard (MSB No.3) installed with the current transformers.
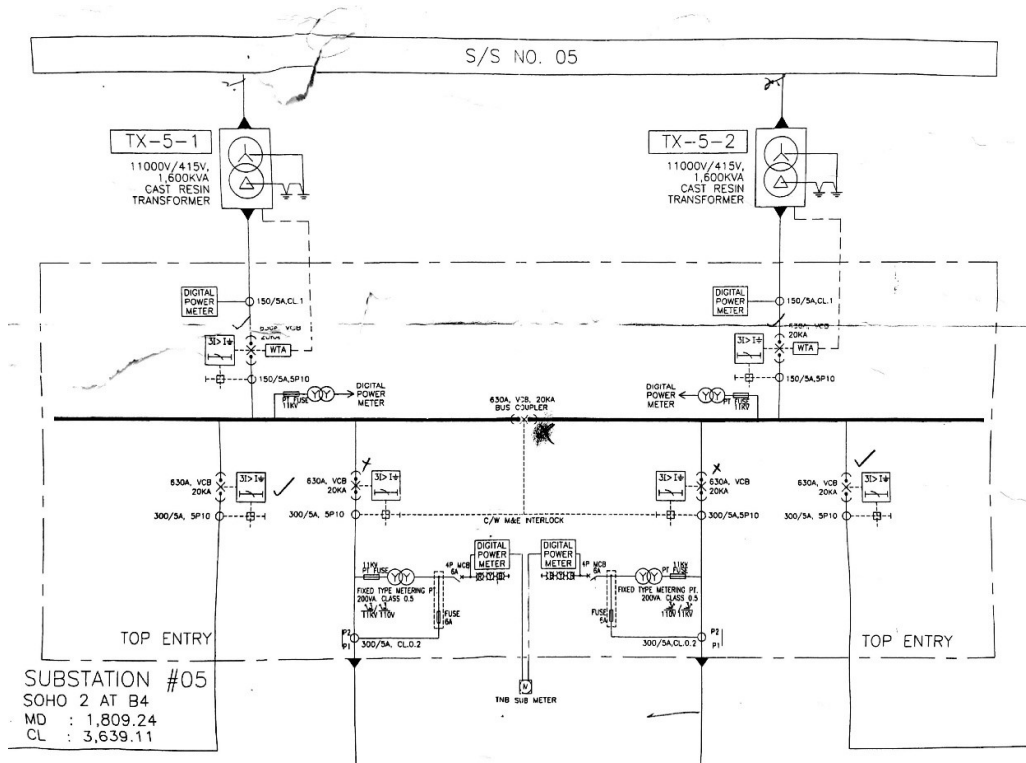

Figure 2.14   Substation No.3 Switchgear panel schematic diagram

Figure 2.15   Switchgear panels for Substation No.3.

Figure 2.16   Transformer TX3-1 & TX 3-2.

Substation no.4 as shown in the Figure 2.18 schematic, consist of 4 nos. of 11kV switchgears which consist of 2 incoming feeders and 2 outgoing feeders. The 2 nos. of incoming feeders are connected to Substation No.6 and Substation No.3 respectively. The outgoing feeders serves the 2 nos. of 11kV/415V transformers namely TX 4-1 & TX 4-2 as shown in the Figure 2.18, which are both rated at 1600kVA. There are 2 electric meters as shown in the Figure 2.26 monitoring the consumptions at both the incomings of low voltage switchboard (MSB No.4) installed with the current transformers.
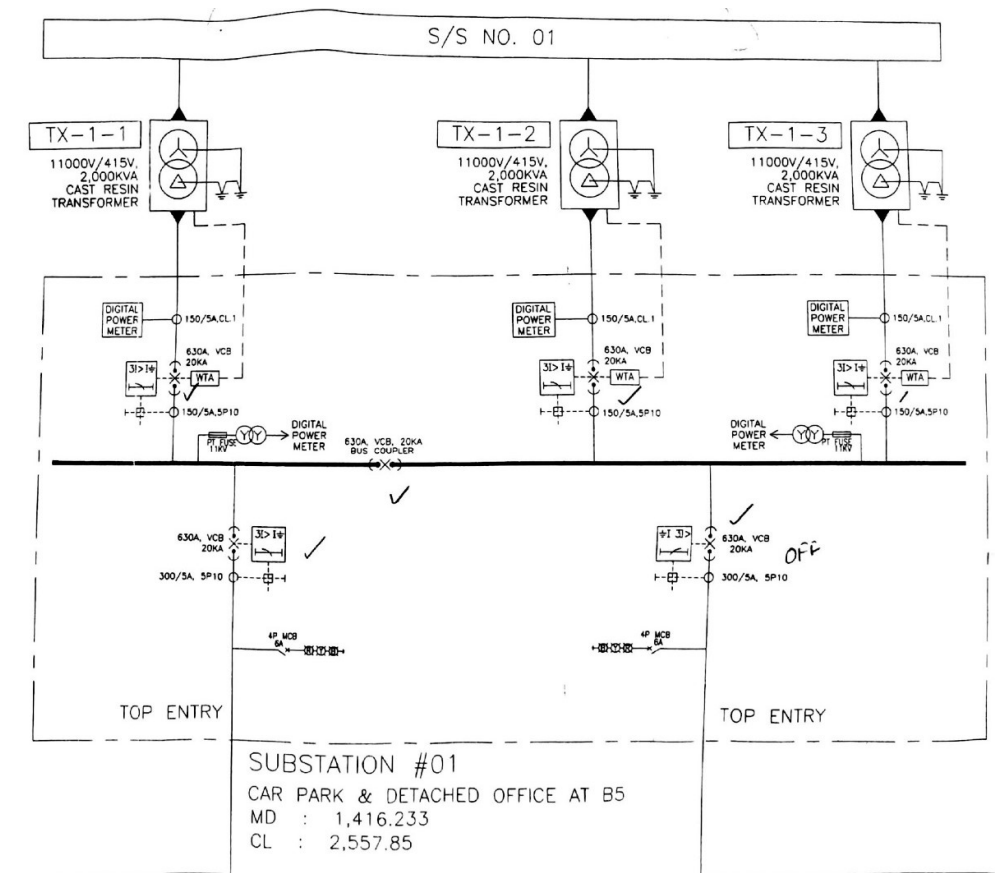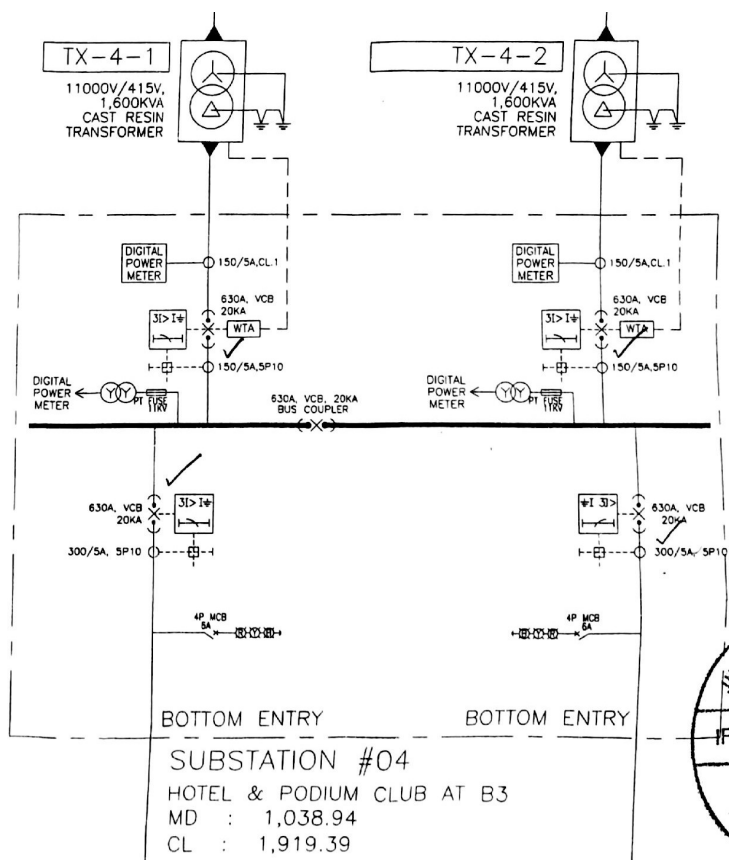

Figure 2.17   Substation No.4 Switchgear panel schematic diagram

Figure 2.18   Substation No.4 Switchgear panel & Transformer TX1-1 & 1-2

Substation no.6 as shown in the Figure 2.19 schematic, consist of 4 nos. of 11kV switchgears which consist of 2 incoming feeders and 2 outgoing feeders as shown in the Figure 2.20. The 2 nos. of incoming feeders are connected to Substation No.5 and Substation No.4 respectively. The outgoing feeders serves the 2 nos. of 11kV/415V transformers namely TX 6-1 & TX 6-2 as shown in the Figure 2.21, which are both rated at 1600kVA. There are 2 electric meters as shown in Figure 2.28 monitoring the consumptions at both the incomings of low voltage switchboard (MSB No.4) installed with the current transformers.
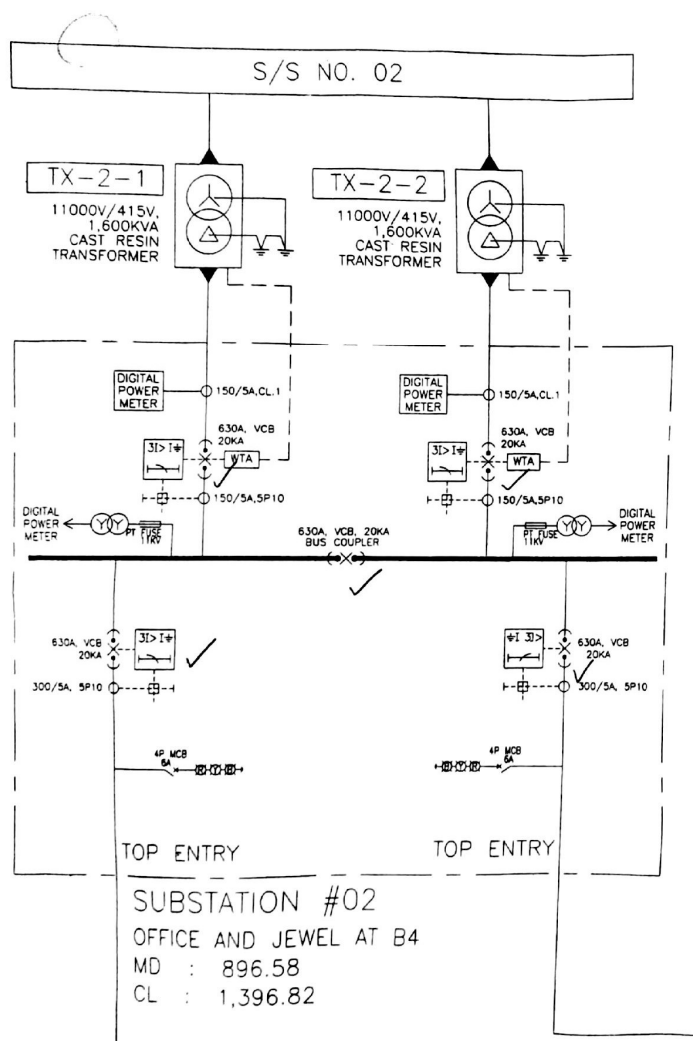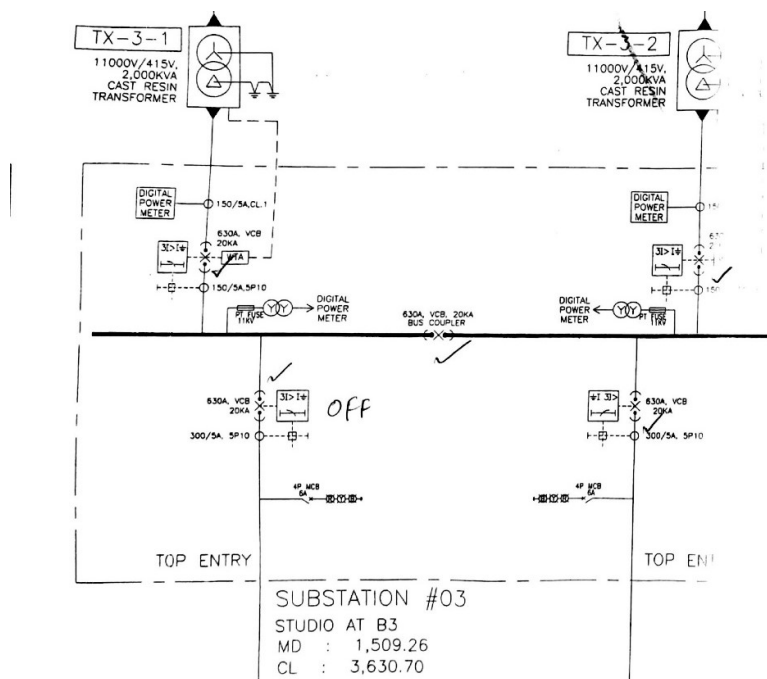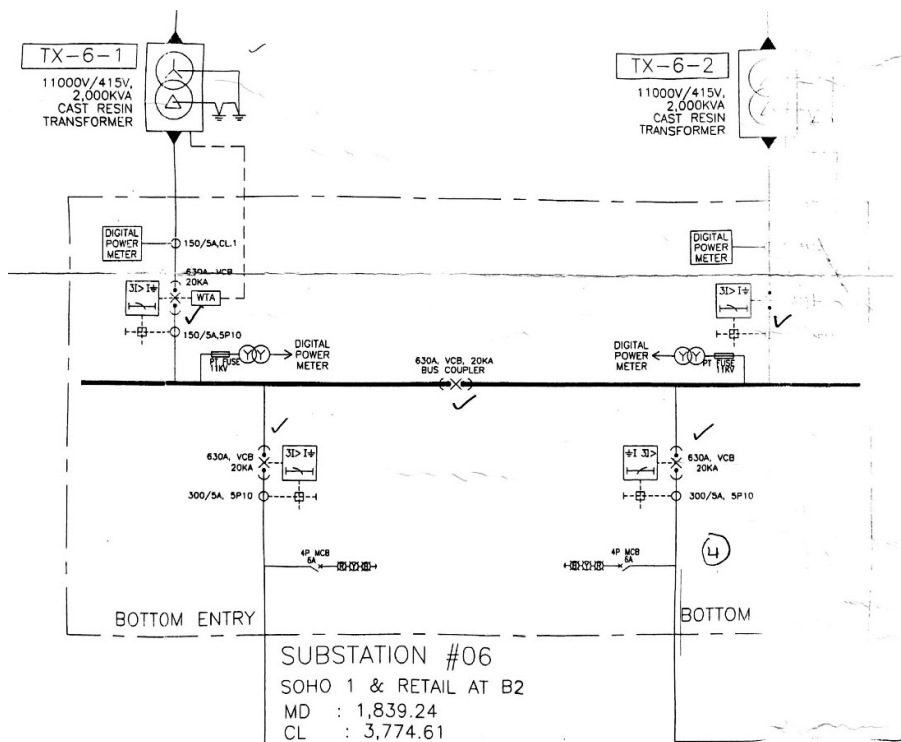
Figure 2.19   Substation No.6 Switchgear panel schematic diagram

Figure 2.20   Substation No.6 Switchgear panel.

Figure 2.21   Transformer TX 6-1 & 6-2

The meters installed for the respective substations are as follow:-

1. TX 1-1 – Meter no. 3810157
2. TX 1-2 – Meter no. 3810158
3. TX 1-3 – Meter no. 3787827
4. TX 2-1 – Meter no. 3810865
5. TX 2-2 – Meter no. 3787867
6. TX 3-1 – Meter no. 3787828
7. TX 3-2 – Meter no. 3787827
8. TX 4-1 – Meter no. 3787824
9. TX 4-2 – Meter no. 3810861
10. TX 5-1 – Meter no. 3787831
11. TX 5-2 – Meter no. 3787830
12. TX 6-1 – Meter no. 3810864
13. TX 6-2 – Meter no. 3810862

Figure 2.22   Metering panels for TX 1-1, 1-2 & 1.3.
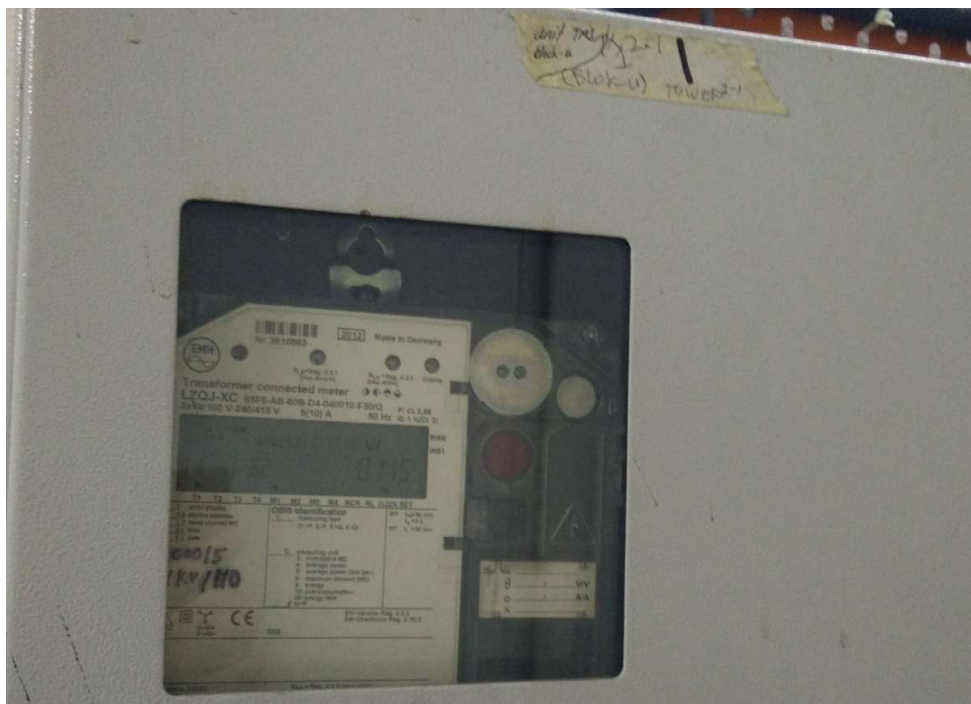
Figure 2.23   Metring panel for TX 2-1

Figure 2.24   Metering panel for TX 2-2

Figure 2.25   Metering panel for TX 3-1 & TX 3-2

Figure 2.26   Metering panel for TX 4-1 & TX 4-2

Figure 2.27   Metering panel for TX 5-1 & TX 5-2

Figure 2.28   Metering panel for TX6-1 & TX 6-2

CHAPTER 3

METHODOLOGY

3.1 Research Methods

The method of the research for the project is to build a model to forecast the medium term loads of a mix development project or commercial project to predict the load demands based on previous data obtained. Matlab simulations is used to predict the values of future load demands. The model used is the nonlinear neural network model with two hidden layers & open loop during training as shown in Figure 3.1. The Levenberg-Marquardt algorithm for back propagations is used as the training functions for the network. The data is split between training, validations and test. The training of function is continued until one of the performance functions are achieved for example an increase in the mean squared error indicates that it has achieved the best function performance. After completion of the training, the function is converted into close loop as shown in Figure 3.2 and use to forecast future values. Optimizations of the function is done by adjusting the values of the delays for the inputs and feedback also the no. of neurons used for the hidden layer.
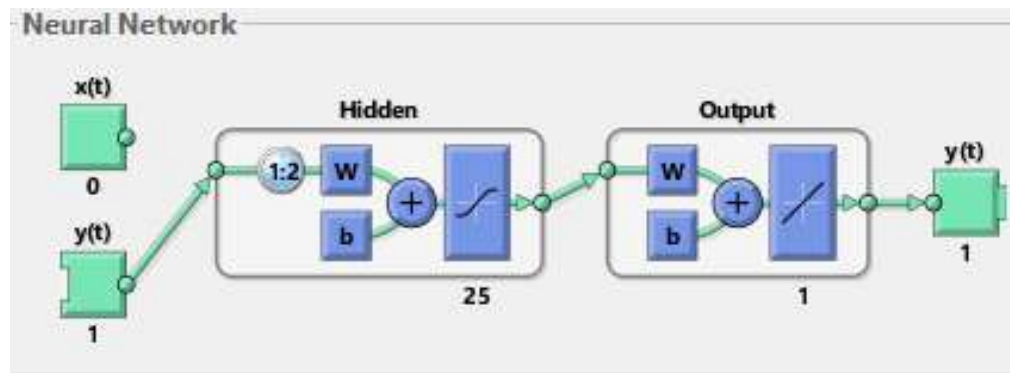
Figure 3.1   Neural network with 2 layers, Hidden layer comprise of 25 neurons.
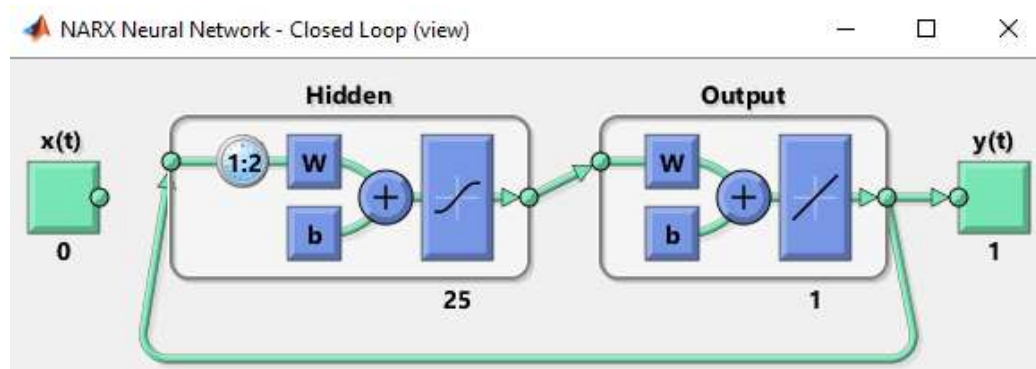
Figure 3.2   Neural network with close loop, for predicting future values.

CHAPTER 4

RESULTS AND DISCUSSION

4.1   Data collected from Empire Damansara

Courtesy of Mammoth Empire Holdings Sdn.Bhd. The data is taken from each of the bulk meters for that reads the output of each transformer at each substation and consolidated into a table as shown in Table 2.1.

Month	kWH		Month	kWH		Month	kWH
Jan-13	149376		Jan-14	281705		Jan-15	363345
Feb-13	144404		Feb-14	281655		Feb-15	328831
Mar-13	143998		Mar-14	336004		Mar-15	331196
Apr-13	157926		Apr-14	319928		Apr-15	303377
May-13	164808		May-14	352277		May-15	306547
Jun-13	171537		Jun-14	367598		Jun-15	233404
Jul-13	196512		Jul-14	370253		Jul-15	225065
Aug-13	200673		Aug-14	336382		Aug-15	257024
Sep-13	150836		Sep-14	338318		Sep-15	245397
Oct-13	240387		Oct-14	361198		Oct-15	256670
Nov-13	221673		Nov-14	342882		Nov-15	237182
Dec-13	258866		Dec-14	356418		Dec-15	256067

Table 2.1 Data collected from Empire Damansara.

4.2   Empire Damansara Forecast for 3 months

When running the Levenberg-Marquardt function with data distributions of 80% for training, 10% for validations and 10% for testing. For input delays of 1, and size of hidden layer of 5 neurons. The results observed after 57 iterations as shown in Figure 4.1, after achieving the best validation performance at epoch 6 with MSE of 2.07E+09 as shown in Figure 4.2. Using values were taken from Figure 4.3 for calculating the mean average percentage error, the errors for the test values are 4.65%. The total regressions is 0.98807 which indicates that the overall fit of the functions is very good as shown in Figure 4.4.

Figure 4.1   Function model & performance.

Figure 4.2   Best MSE Validation performance.

Figure 4.3   Time Series Output.

Figure 4.4   Regression plot

4.3 Empire Damansara Forecast for 6 months

When running the Levenberg-Marquardt function with data distributions of 70% for training, 5% for validations and 25% for testing.

For input delays of 2, and size of hidden layer for 3 neurons. The results observed after 16 iterations as shown in Figure 4.5, after achieving the best validation performance at epoch 10 with MSE of 2.05E+09 as shown in Figure 4.6. Using values were taken from Figure 4.7 for calculating the mean average percentage error, the errors for the test values are 3.87 %. The total regressions is 0.98923 which indicates that the overall fit of the functions is very good as shown in Figure 4.8.

Progress			
Epoch:	0	16 iterations	1000
Time:		0:00:00	
Performance:	6.02e+11	2.02e+09	0.00
Gradient:	1.13e+12	4.86e+08	1.00e-07
Mu:	0.00100	1.00e+07	1.00e+10
Validation Checks:	0	6	6

Figure 4.5   Function model & performance.

Figure 4.6   Best MSE Validation performance.

Figure 4.7   Time Series Output.
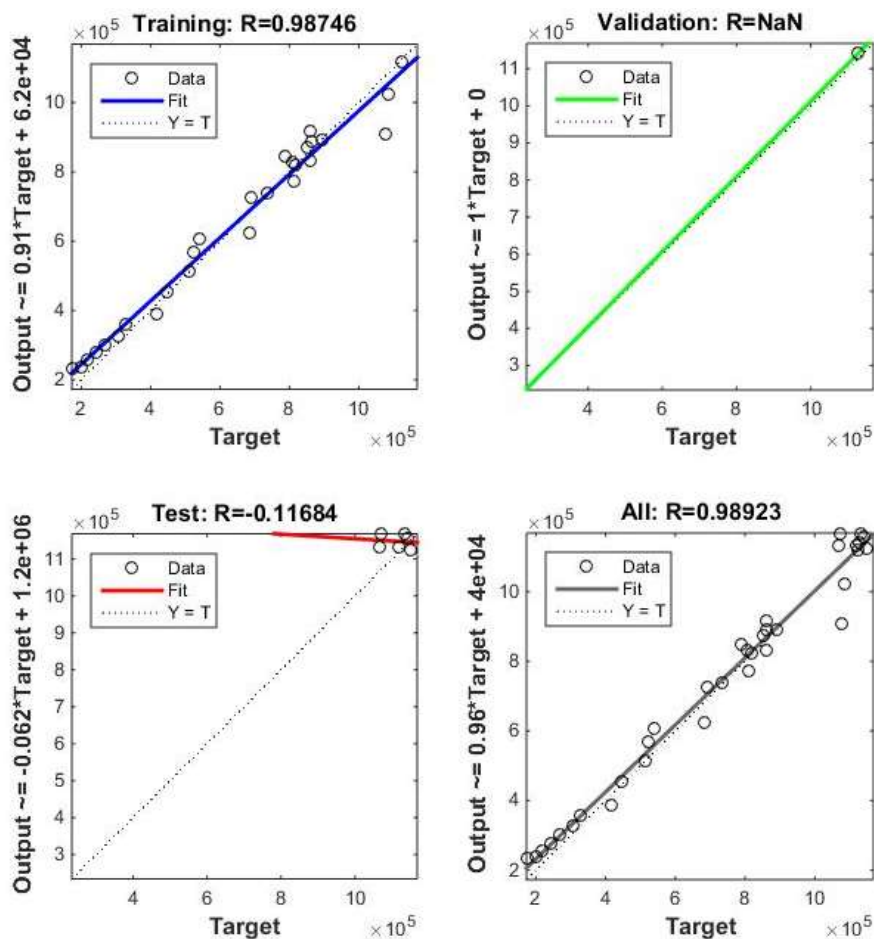
Figure 4.8   Regression plot

4.4   Empire Damansara Forecast for 8 months

When running the Levenberg-Marquardt function with data distributions of 65% for training, 5% for validations and 25% for testing.

For input delays of 2, and size of hidden layer for 3 neurons. The results observed after 10 iterations as shown in Figure 4.9, after achieving the best validation performance at epoch 6 with MSE of 2.42E+09 as shown in Figure 4.10. Using values were taken from Figure 4.11 for calculating the mean average percentage error, the errors for the test values are 3.54%. The total regressions is 0.99051 which indicates that the overall fit of the functions is very good as shown in Figure 4.12.
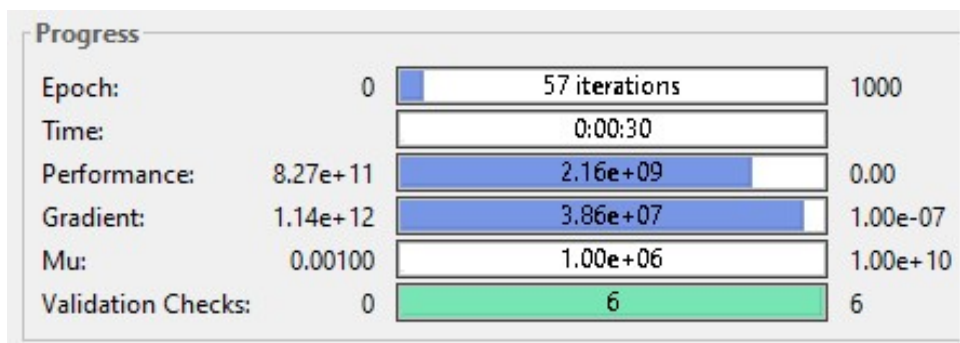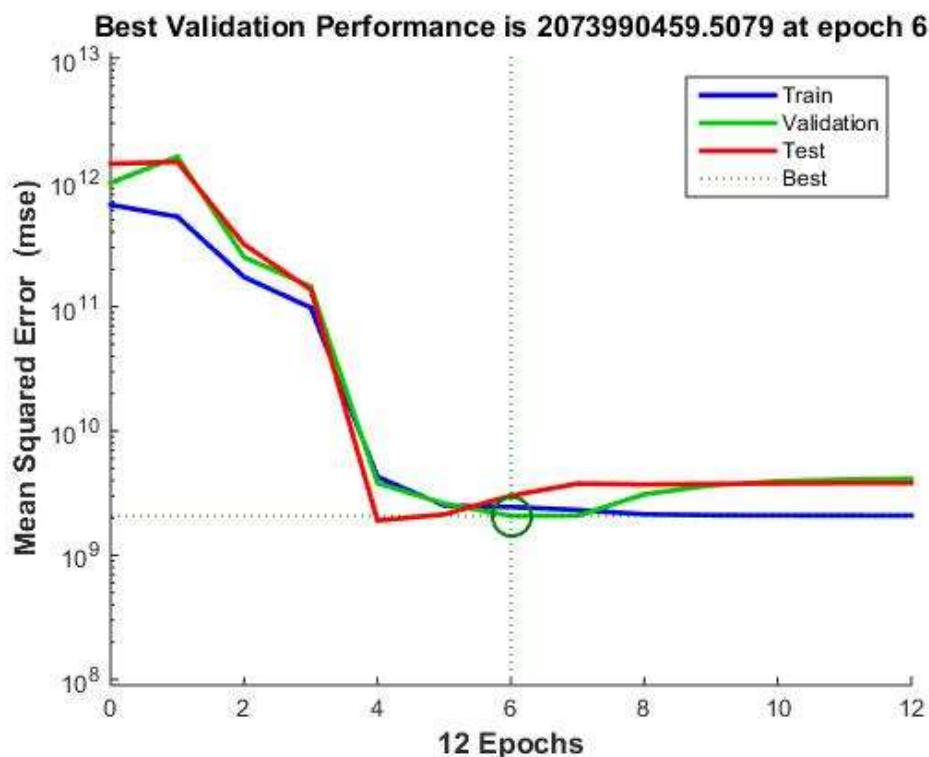
Figure 4.9   Function model & performance.

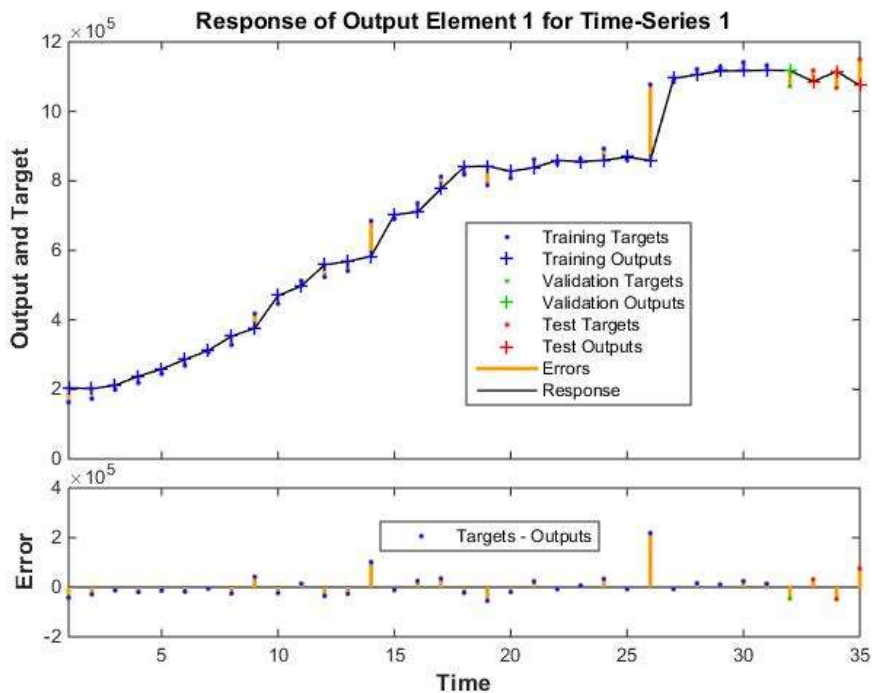Figure 4.10   Best MSE Validation performance.
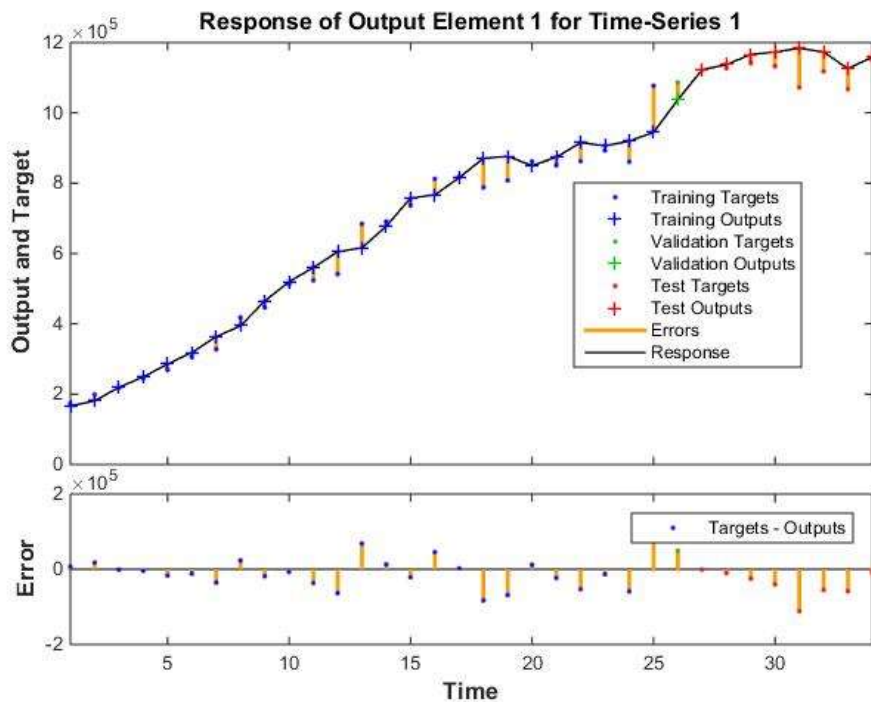
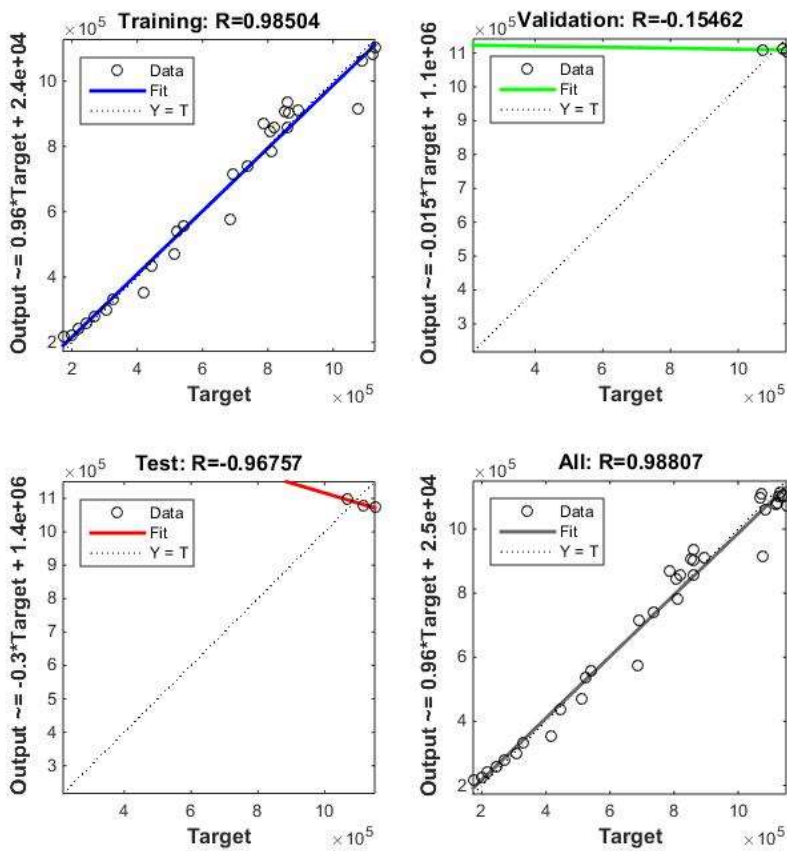Figure 4.11   Time Series Output.
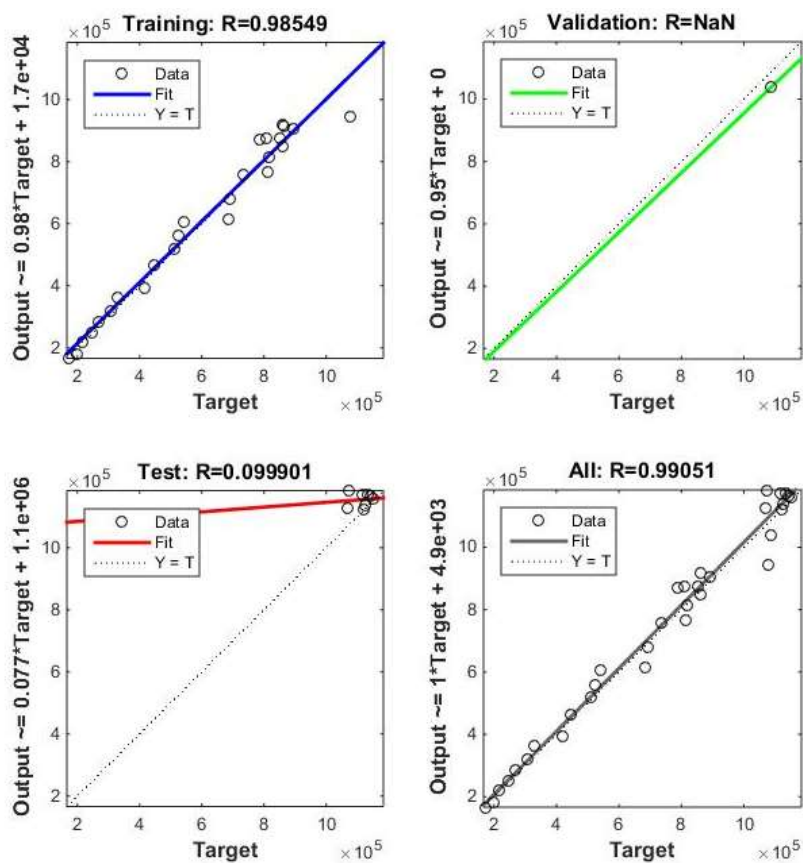
Figure 4.12   Regression plot

4.5   **Empire Damansara Forecast for 12 months**

When running the Levenberg-Marquardt function with data distributions of 50% for training, 13% for validations and 37% for testing. There was some issues encountered due to the spike in the data. This is because the load of the hotel component drastically picked up in the final year and because the loop is closed when the function started to generate the predicted values. Using this data to generate the test data, the curve is offset significantly from the targeted data curve. Therefore, the data for the hotel component was scaled to minimize the effect on the test accuracy.

For input delays of 1, and size of hidden layer for 3 neurons. The results observed after 11 iterations as shown in Figure 4.13, after achieving the best validation performance at epoch 6 with MSE of 7.25E+08 as shown in Figure 4.14. Using values were taken from Figure 4.15 for calculating the mean average percentage error, the errors for the test values are 5.24%. The total regressions is 0.98861 which indicates that the overall fit of the functions is very good as shown in Figure 4.16.
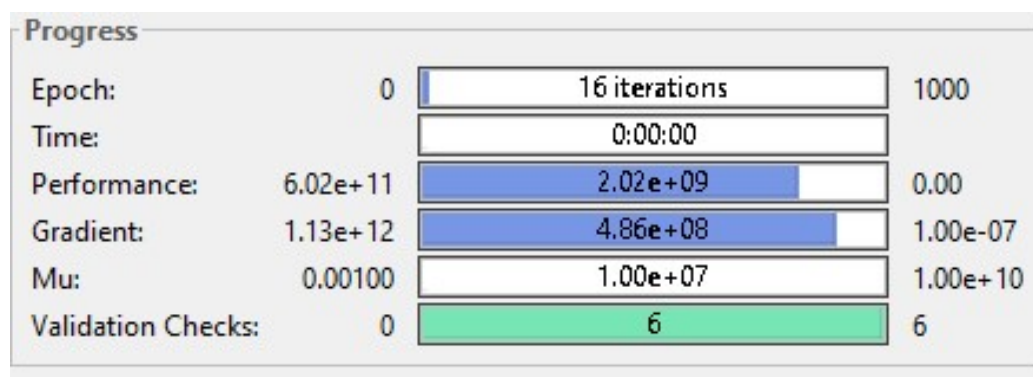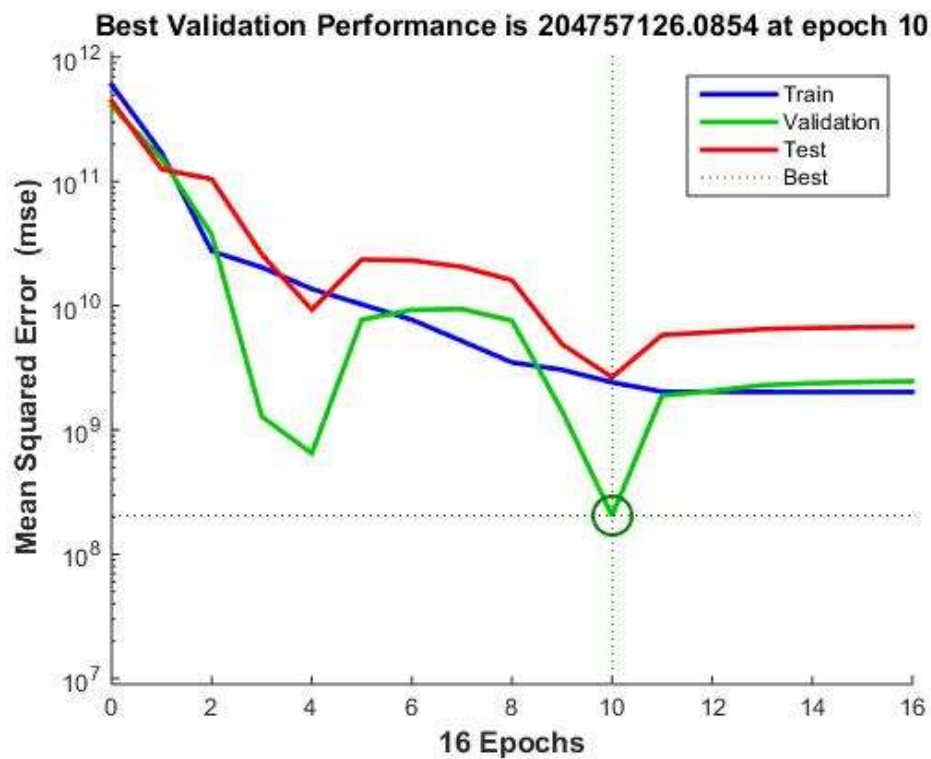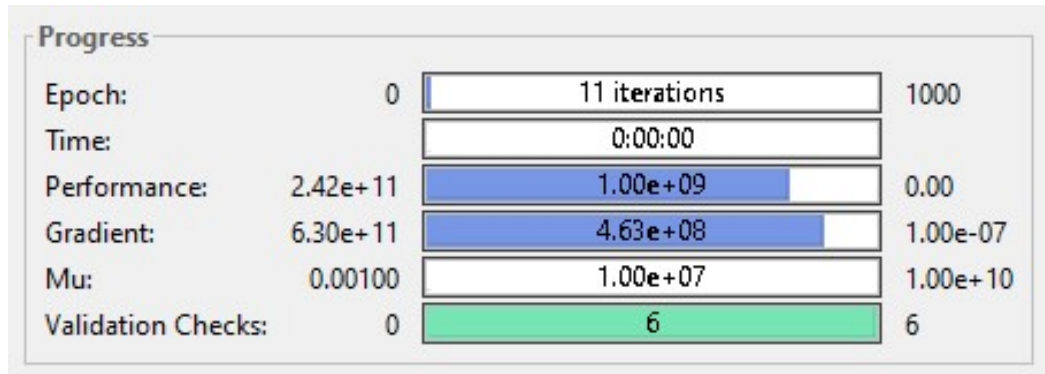

Figure 4.13   Function model & performance.
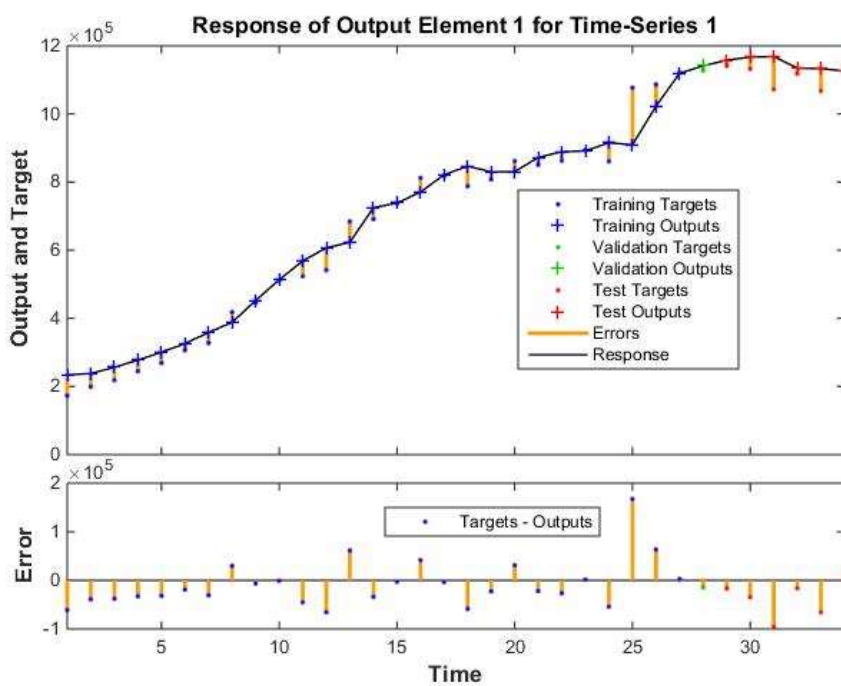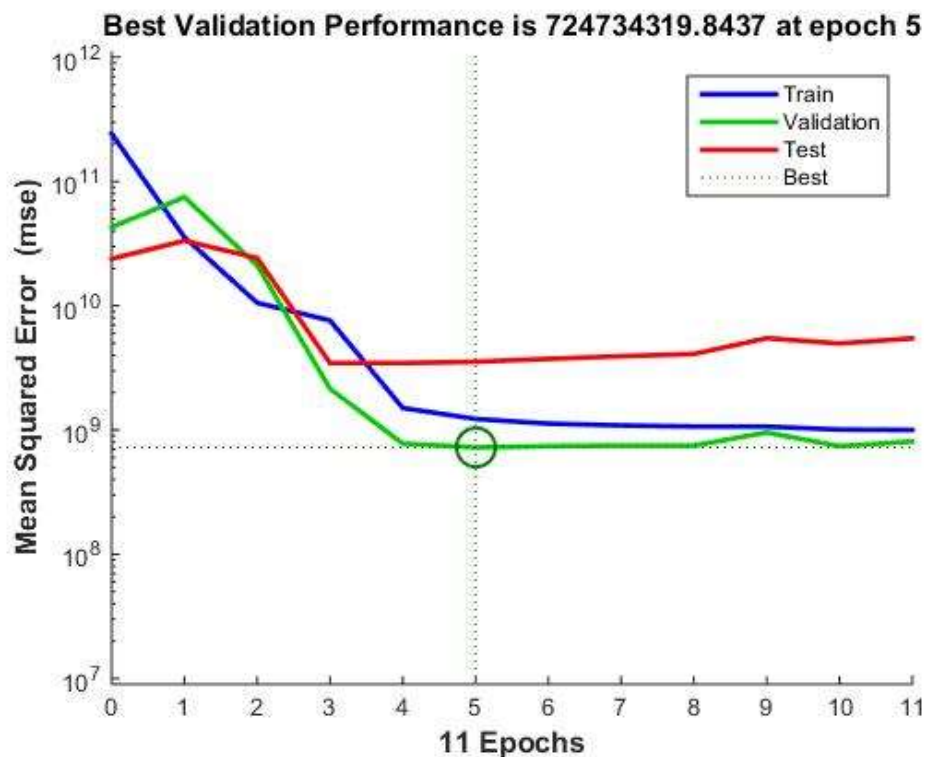
Figure 4.14   Best MSE Validation performance.
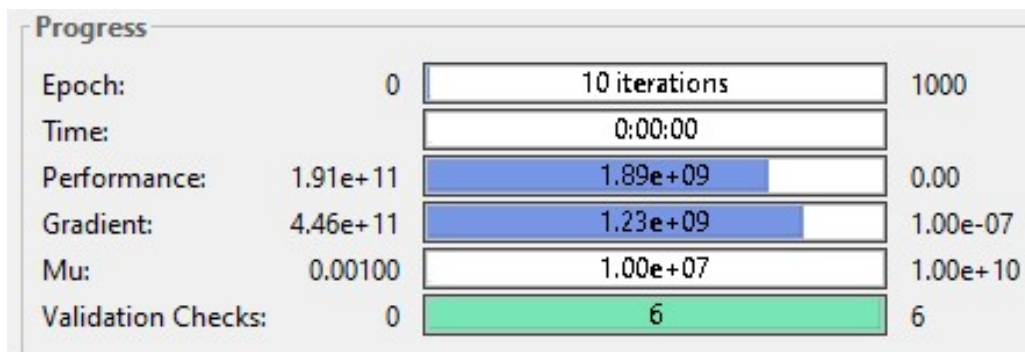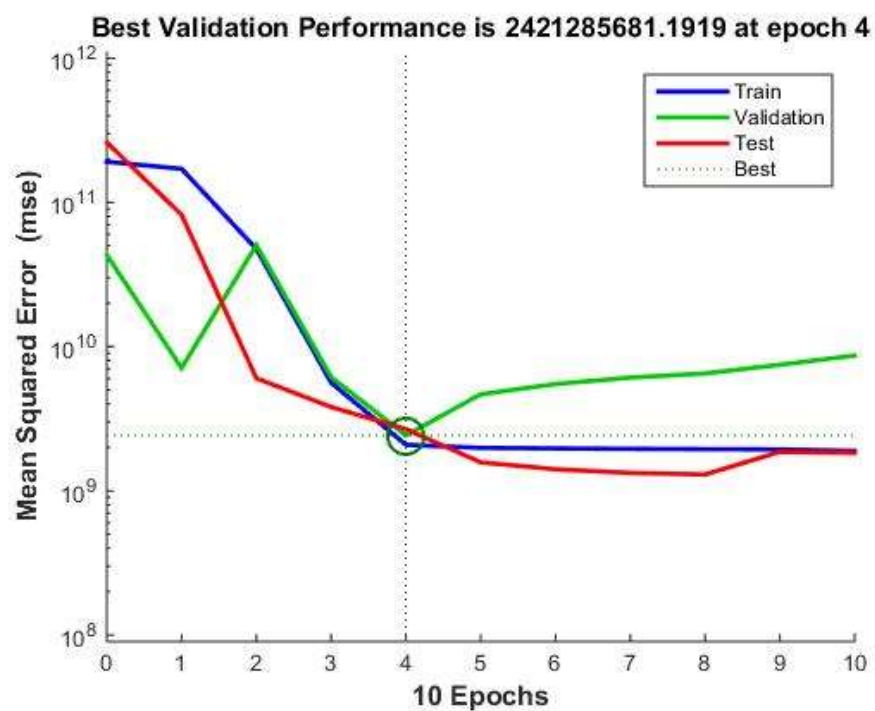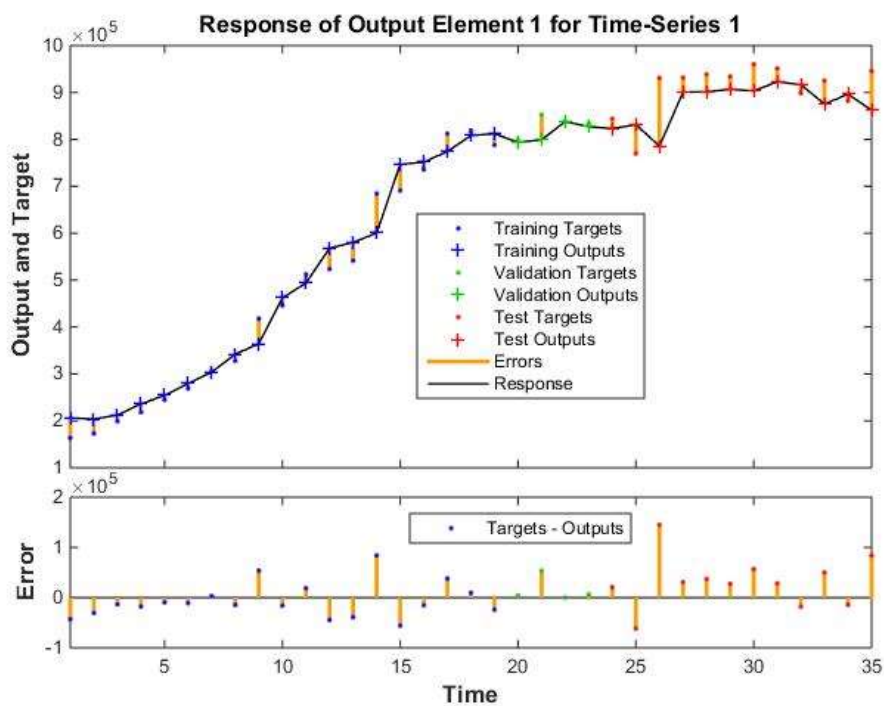

Figure 4.15   Time Series Output.
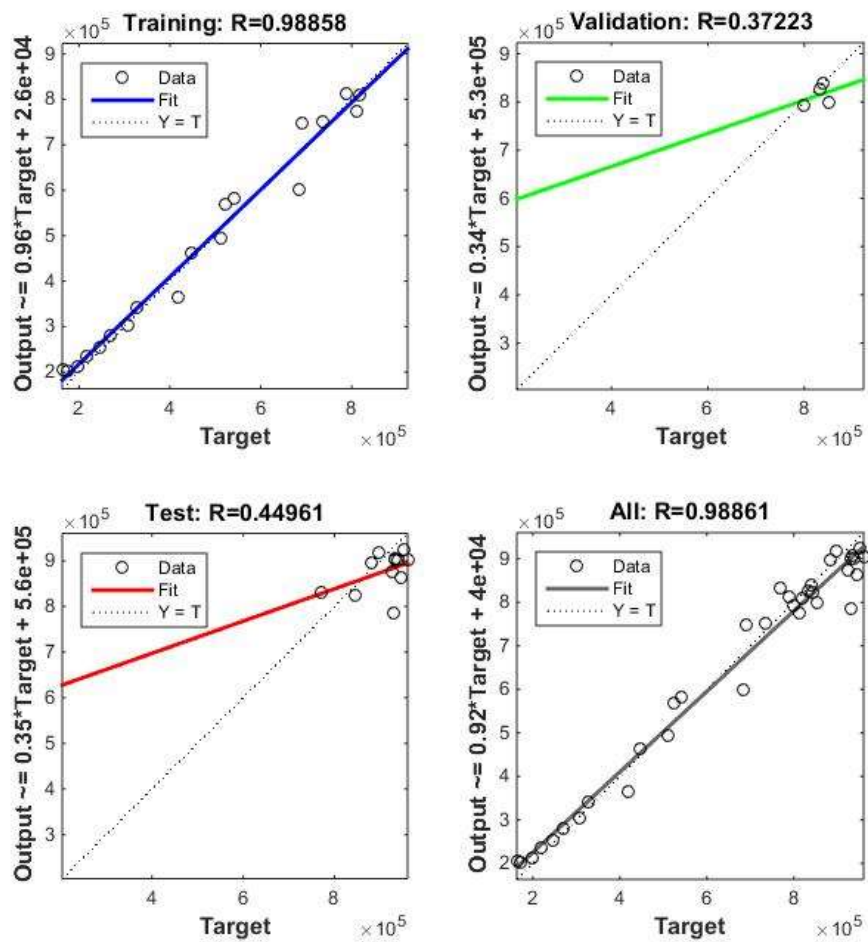
Figure 4.16   Regression plot

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1   Conclusion

The results from training, validations and testing the data collected, it is observed that the Levenberg-Marquardt algorithm which include into the back propagation NN is able to predict the values within reasonable fair errors. By closing the loop after training and validations, the function is able to output data that is close to that of the target values. Although the data collected does not have many points, but the Levenberg-Marquardt function proved that it is able to cope even with limited data input and is able to predict up 12 months without much errors. The mix development data profile looks to be healthy and increasing year-on-year.

5.2   Recommendations

To yield more accurate results, more data points for forecasting may be required. There seems to be some times where the function where it over compensated and large error values were observed but by re-training a few times it turns out to be just random and rare occurrence. It might also help to have the load weightage for each component of data, this will helps for future forecasting to incorporate different components in the system.

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APPENDICES

A. TNB ELECTRICY TARIFF SCHEDULE

Commercial Tariffs

Tariff B - Low Voltage Commercial Tariff

For the first 200 kWh (1 -200 kWh) per month	43.5 sen/kWh
For the next kWh (201 kWh onwards) per month	50.9 sen/kWh

The minimum monthly charge is RM7.20

Tariff C1 - Medium Voltage General Commercial Tariff

For each kilowatt of maximum demand per month	30.3 RM/kW
For all kWh	36.5 sen/kWh

The minimum monthly charge is RM600.00

Tariff C2 - Medium Voltage Peak/Off-Peak Commercial Tariff

For each kilowatt of maximum demand per month during the peak period

	45.1 RM/kW
For all kWh during the peak period	36.5 sen/kWh
For all kWh during the off-peak period	22.4 sen/kWh

The minimum monthly charge is RM600.00

Industrial Tariffs

Tariff D - Low Voltage Industrial Tariff

For the first 200 kWh (1 -200 kWh) per month	38.00 sen/kWh
For the next kWh (201 kWh onwards) per month	44.10 sen/kWh

The minimum monthly charge is RM7.20

Tariff Ds – Special Industrial Tariff (for consumers who qualify only)

For all kWh   42.70 sen/kWh

The minimum monthly charge is RM7.20

Tariff E1 - Medium Voltage General Industrial Tariff

For each kilowatt of maximum demand per month   29.60 RM/kW

For all kWh   33.70 sen/kWh

The minimum monthly charge is RM600.00

Tariff E1s – Special Industrial Tariff (for consumers who qualify only)

For each kilowatt of maximum demand per month   23.70 RM/kWh

For all kWh   33.60 sen/kWh

The minimum monthly charge is RM600.00

Tariff E2 - Medium Voltage Peak/Off-Peak Industrial Tariff

For each kilowatt of maximum demand per month during the peak period

                                                               37.00 RM/kW

For all kWh during the peak period   35.50 sen/kWh

For all kWh during the off-peak period   21.90 sen/kWh

The minimum monthly charge is RM600.00

Tariff E2s – Special Industrial Tariff (for consumers who qualify only)

For each kilowatt of maximum demand per month during the peak period

                                                               32.90 RM/kW

For all kWh during the peak period   33.60 sen/kWh

For all kWh during the off-peak period   19.10 sen/kWh

The minimum monthly charge is RM600.00

Tariff E3 - High Voltage Peak/Off-Peak Industrial Tariff

For each kilowatt of maximum demand per month during the peak period   35.50
RM/kW

For all kWh during the peak period   33.70 sen/kWh

For all kWh during the off-peak period   20.20 sen/kWh

The minimum monthly charge is RM600.00

Tariff E3s – Special Industrial Tariff (for consumers who qualify only)

For each kilowatt of maximum demand per month during the peak period   29.00 RM/kW

For all kWh during the peak period   31.70 sen/kWh

For all kWh during the off-peak period   17.50 sen/kWh

The minimum monthly charge is RM600.00

Mining Tariffs

Tariff F - Low Voltage Mining Tariff

For all kWh   38.10 sen/kWh

The minimum monthly charge is RM120.00

Tariff F1 - Medium Voltage General Mining Tariff

For each kilowatt of maximum demand per month   21.10 RM/kW

For all kWh   31.30 sen/kWh

The minimum monthly charge is RM120.00

Tariff F2 - Medium Voltage Peak/Off-Peak Mining Tariff

For each kilowatt of maximum demand per month during the peak period

                                                                        29.80 RM/kW

For all kWh during the peak period   31.30 sen/kWh

For all kWh during the off-peak period   17.20 sen/kWh

The minimum monthly charge is RM120.00

Specific Agricultural Tariffs

Tariff H – Low Voltage Specific Agriculture Tariff

For the first 200 kWh (1 -200 kWh) per month   39.00 sen/kWh

For the next kWh (201 kWh onwards) per month   47.20 sen/kWh

The minimum monthly charge is RM7.20

Tariff H1 - Medium Voltage General Specific Agriculture Tariff

For each kilowatt of maximum demand per month   30.30 RM/kW

For all kWh   35.10 sen/kWh

The minimum monthly charge is RM600.00

Tariff H2 - Medium Voltage Peak/Off-Peak Specific Agriculture Tariff

For each kilowatt of maximum demand per month during the peak period

                                               40.80 RM/kW

For all kWh during the peak period   36.50 sen/kWh

For all kWh during the off-peak period   22.40 sen/kWh

The minimum monthly charge is RM600.00

For Co-generators, Top-up Supply and Standby Supply Tariffs

TARIFF CATEGORY	UNIT	CURRENT RATE (1 Jan 2014)	
		Top-Up	Standby
Tariff C1 - Medium Voltage General Commercial Tariff			
Maximum demand charge per month	RM/kW	30.3	14
Tariff C2 - Medium Voltage Peak/Off-Peak Commercial Tariff			
For each kilowatt of maximum demand per month during the peak period	RM/kW	45.1	14
Tariff E1 - Medium Voltage General Industrial Tariff			
Maximum demand charge per month	RM/kW	29.6	14
Tariff E2 – Medium Voltage Peak/Off-Peak Industrial Tariff			
For each kilowatt of maximum demand per month during the peak period	RM/kW	37	14
Tariff E3 – High Voltage Peak/Off-Peak Industrial Tariff			
For each kilowatt of maximum demand per month during the peak period	RM/kW	35.5	12
Tariff F1 – Medium Voltage General Mining Tariff			
Maximum demand charge per month	RM/kW	21.1	14
Tariff F2 – Medium Voltage Peak/Off-Peak Mining Tariff			
For each kilowatt of maximum demand per month during the peak period	RM/kW	29.8	14
Tariff H1 – Medium Voltage General Specific Agriculture Tariff			
Maximum demand charge per month	RM/kW	30.3	14
Tariff H2 – Medium Voltage Peak/Off-Peak Specific Agriculture Tariff			
For each kilowatt of maximum demand per month during the peak period	RM/kW	40.8	14

B. MATLAB CODE

Solve an Autoregression Problem with External Input with a NARX Neural Network

```
%
%   t - input time series.
%   kWh - feedback time series.

X = tonndata(t(1:end,2:end),false,false);
T = tonndata(kWh(1:end,1),false,false);

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. NTSTOOL falls back to this in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt


for k = 1
    for j = 2

% Create a Nonlinear Autoregressive Network with External Input
inputDelays = 1:j;
feedbackDelays = 1:j;
hiddenLayerSize = 25*k;

net = narxnet(inputDelays,feedbackDelays,hiddenLayerSize,'open',trainFcn);

% Choose Input and Feedback Pre/Post-Processing Functions
% Settings for feedback input are automatically applied to feedback output
% For a list of all processing functions type: help nnprocess
% Customize input parameters at: net.inputs{i}.processParam
% Customize output parameters at: net.outputs{i}.processParam
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
```

```
net.inputs{2}.processFcns = {'removeconstantrows','mapminmax'};
```

```
% Prepare the Data for Training and Simulation
% The function PREPARETS prepares timeseries data for a particular network,
% shifting time by the minimum amount to fill input states and layer states.
% Using PREPARETS allows you to keep your original time series data unchanged, while
% easily customizing it for networks with differing numbers of delays, with
% open loop or closed loop feedback modes.
[x,xi,ai,t] = preparets(net,X,{},T);
```

```
% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
% The property DIVIDEMODE set to TIMESTEP means that targets are divided
% into training, validation and test sets according to timesteps.
% For a list of data division modes type: help nntype_data_division_mode
net.divideMode = 'value';  % Divide up every value
net.divideFcn = 'divideblock';
net.divideParam.trainRatio = 55/100;
net.divideParam.valRatio = 10/100;
net.divideParam.testRatio = 35/100;
```

```
% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
% Customize performance parameters at: net.performParam
net.performFcn = 'mse';  % Mean squared error
```

```
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
% Customize plot parameters at: net.plotParam
net.plotFcns = {'plotperform','plottrainstate','plotresponse', ...
  'plotregression','ploterrcorr', 'plotinerrcorr'};
```

```
% Train the Network
```

```
[net,tr] = train(net,x,t,xi,ai);


% Test the Network
y = net(x,xi,ai);
e = gsubtract(t,y);
performance = perform(net,t,y)


% Recalculate Training, Validation and Test Performance
trainTargets = gmultiply(t,tr.trainMask);
valTargets = gmultiply(t,tr.valMask);
testTargets = gmultiply(t,tr.testMask);
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)


% View the Network
view(net)


% Closed Loop Network
% Use this network to do multi-step prediction.
% The function CLOSELOOP replaces the feedback input with a direct
% connection from the outout layer.
netc = closeloop(net);
netc.name = [net.name ' - Closed Loop'];
view(netc)
[xc,xic,aic,tc] = preparets(netc,t,{},kWh);
yc = netc(xc,xic,aic);
closedLoopPerformance = perform(netc,tc,yc)
% Multi-step Prediction
% Sometimes it is useful to simulate a network in open-loop form for as
% long as there is known output data, and then switch to closed-loop form
% to perform multistep prediction while providing only the external input.
% Here all but 5 timesteps of the input series and target series are used to
% simulate the network in open-loop form, taking advantage of the higher
```

```
% accuracy that providing the target series produces:
numTimesteps = size(x,2);
knownOutputTimesteps = 1:(numTimesteps-5);
predictOutputTimesteps = (numTimesteps-4):numTimesteps;
X1 = X(:,knownOutputTimesteps);
T1 = T(:,knownOutputTimesteps);
[x1,xio,aio] = preparets(net,X1,{},T1);
[y1,xfo,afo] = net(x1,xio,aio);
% Next the the network and its final states will be converted to closed-loop
% form to make five predictions with only the five inputs provided.
x2 = X(1,predictOutputTimesteps);
[netc,xic,aic] = closeloop(net,xfo,afo);
[y2,xfc,afc] = netc(x2,xic,aic);
multiStepPerformance = perform(net,T(1,predictOutputTimesteps),y2)
% Alternate predictions can be made for different values of x2, or further
% predictions can be made by continuing simulation with additional external
% inputs and the last closed-loop states xfc and afc.


% Step-Ahead Prediction Network
% For some applications it helps to get the prediction a timestep early.
% The original network returns predicted y(t+1) at the same time it is given y(t+1).
% For some applications such as decision making, it would help to have predicted
% y(t+1) once y(t) is available, but before the actual y(t+1) occurs.
% The network can be made to return its output a timestep early by removing one delay
% so that its minimal tap delay is now 0 instead of 1.  The new network returns the
% same outputs as the original network, but outputs are shifted left one timestep.
nets = removedelay(net);
nets.name = [net.name ' - Predict One Step Ahead'];
% view(nets)
[xs,xis,ais,ts] = preparets(nets,X,{},T);
ys = nets(xs,xis,ais);
stepAheadPerformance = perform(nets,ts,ys)
end
end
```