A COMPARATIVE STUDY BETWEEN WITH AND WITHOUT INFLUENCE OF TEMPERATURE FOR LOAD FORECAST

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Abstract- **Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. Load forecasting has always been the important part of an efficient power system planning and operation. The purpose of this project is to develop an Artificial Neural Network (ANN) to predict the load forecasting in power system by using MATLAB programming. Furthermore, to predict the usage of load for the weekdays approach with and without influence of weather or temperature to the load forecast and get the Mean Absolute Percentage Error (MAPE) below 5% that has been provided by TNB Berhad. These methods can fully recognizing the types of the data in term of training data and test data. All data are taken from Tenaga Nasional Berhad and Jabatan Meteorologi. These methods forecast the demand load by using forecasted temperature as forecast information. Means, when the temperature curves change rapidly on the forecast day, loads change greatly and forecast error would be going to increase.**

Keywords: **Short term load forecasting and Artificial Neural Network (ANN)**

1.0 INTRODUCTION

Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Electrical Short term load forecasting plays an important role for the operation and planning in power system [1]. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets. Exact model for electrical load forecasting are essentially to the operational and planning of the company. For Utilities Company, it likes an advice to help the company to make right decision in term of purchasing and generating power. Load forecast is important for those who involve or participant in electrical energy such as generation, transmission and distribution. Load forecasting also can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts [2]. From the previous analysis this problems can be prevent by obtaining the best mean absolute percentage error for the load forecasting [3].

In peak demand load forecasting, the weather plays an important role [4]. Actually, for many systems the peak

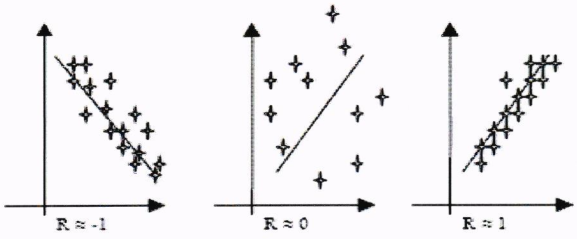

Figure 1: R2 value curves

demand occurs at times when weather-dependent loads, i.e. heating or air-conditioning are switched-on. The reason for the phenomenon is the high penetration of electric space heaters or air conditioners [5]. The total system peak demand can be viewed as the sum of a component which is weather insensitive and another component which is weather sensitive, i.e.,

$$dp(k) = B(k) + W(k)$$

where:

$B(k)$ = Weather-insensitive component in time interval k

$W(k)$ = Weather-sensitive component in time interval k

The weather-sensitive component, W (k), represents the electric power demand of weather sensitive devices, such as space heaters and air conditioners. It depends on weather variables such as:

• Coincident dry-bulb temperature, T

• Humidity, h

• Wind velocity, v, etc

Forecasting models for the weather-sensitive component, W(k), follow the same principles as the models for forecasting the non weather-sensitive component B(k). Specifically, a model is assumed, the parameters of the model are identified using past data and then the model is used to predict future loads. To identify the weather-sensitive component, the total demand is sampled (hourly, daily, weekly, annually) together with weather variables. Usually the daily or weekly peaks are recorded. Then model identification procedures can be employed to separate the non weather-sensitive component from the weather sensitive component.

Previous approaches can be generally classified into two categories in accordance with techniques they employ [6]. The modern approach also known as Artificial Intelligent (AI) technique recognizes that the load pattern is heavily dependent on the non-linear variables such as weather, and finds a functional relationship between the variables and the system load compare [7]. One of the AI techniques that are familiar in load forecasting method is Artificial Neural Network (ANN). The neural network is able to learn how to perform a task by automatically changing the values of its weights

This paper presents an application of Artificial Neural Network (ANN) by using back propagation to solve load forecasting problem. The neural network is able to learn how to perform a task by automatically changing the values of its weights [8]. The developed ANN by using MATLAB programming was used to determine the predicted power or demand to be generated by the system in a power generation system. With the proposed method, the mean absolute forecasting error was below 5%. These methods forecast the demand power by using forecasted temperature as forecast information. But, when the temperature curves change rapidly on the forecast day, loads change greatly and forecast error would be going to increase. Typically, load forecasting can be long-term, medium-term, short-term or very short-term. This paper concentrates on short-term load forecasting

2.0 STLF BY NEURAL NETWORK

Short-term load forecasting has become an important part of modern forecasting method. Several forecasting methods have been widely used in load forecasting prediction, such as time series method, least square method, neural network and others. But some electrical utilities still use conventional method forecasts an electric load of the future day or week. The general concept of neural network is shown in Figure 1 below. The input is different depends on each model such as load, temperature, and others. The output is the forecasted load for future corresponds to forecasted load of specific hour [9].

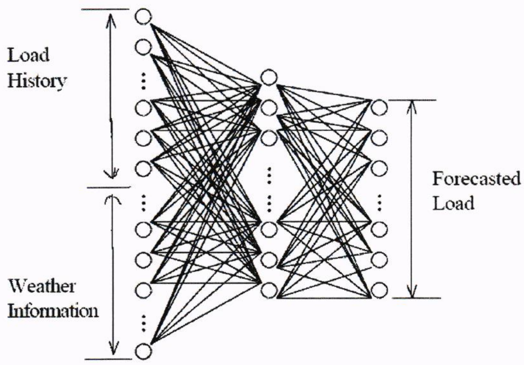

Figure 2: General concepts of ANN

A generic feed forward neural network (FNN) is shown in Figure 3 below shows the input, hidden and output layer of processing elements. The concept of artificial neural network basically is from multiple regression analysis and it is an information processing device, which are created from interconnect elementary processing devices call neurons. Processing elements in an ANN are also known as neurons. Each neuron can have multiple inputs while there can be only one output [10]. Inputs could be from external stimulation or from output of other neurons. The case that output could be input to itself as a feedback is called self recurrent neural network.

Artificial Neural Networks have parallel and distributed processing structures. In addition, a linear transfer function from the input layer directly to the output layer

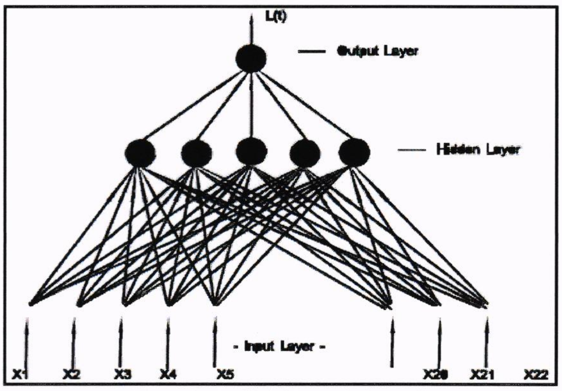

Figure 3: Artificial Neural Network

There is the weight connected with each of every connection. When the weighted sum of the inputs to a neuron exceeds the limit, output signal is produced. When the weights are adjusted, the network can recognize input patterns via learning processes. Normally, method that always been used in training is the back propagation learning algorithm.

3.0 THE LOAD FORECASTING FACTOR AND PERFORMANCE

For short-term load forecasting several factors should be considered, such as time factors, weather data, and possible customers' classes. The medium- and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, the appliance sales data, and other factors. The time factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence.

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts. Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors. Among the weather variables listed, two composite weather variable functions, the THI (temperature-humidity index) and WCI (wind chill index), are broadly used by utility companies. THI is a measure of summer heat discomfort and similarly WCI is cold stress in winter.

3.1 Factor Input

In this project, one of the input data of neural network for load forecast is temperature. Although temperature has been chosen to be one of the inputs, there are still some other factors that can be considered to be an input such rain fall, humidity and wind speed.

3.2 Holiday

In this project, all holiday data can be ignored because data holiday cannot be used to forecast. From the load curve of holidays differ from a typical weekdays, also number of these days in historical information in compression with a typical weekdays is less. Because of abnormal load behavior in these days and not enough samples neural network can't trained. Besides, by comparing the holiday data with normal data there are consist of much difference value.

3.3 Performance

Mean absolute percentage error is a measure of accuracy in a fitted time series value in statistics, specifically trending. It usually expresses accuracy as a percentage.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

The difference between actual value A_t and the forecast value F_t, is divided by the actual value A_t again. The absolute value of this calculation, and divided again by the number of fitted point's n. The purpose of MAPE is to see the percentage error of forecasting by comparing actual data and predict data. In this project, the best MAPE is below 5%.Means that value that less than 5% is the best value.

4.0 DEVELOPMENT OF ANN SYSTEM USING MATLAB

The ANN is assumed as a powerful method and its ability to create a forecasting model automatically by training with actual data. ANN training data are observed for a few weeks. In order to expand learning pattern, an actual data from the same period of previous several years set as training data. Figure 4 below shows the flow chart of the programming that has been developed by using MATLAB programming. The solution must be continually improving.

4.1 Initialization

Get and read all data from file that has been saved in Microsoft excel include train data and test data. Then it will separate the data into two such as input data for train and test data and the other one is output for train and test data.

4.2 Normalize

This part will identify data from Microsoft excel and try to normalize all value data. It means that this process is reducing amount of value from data that is in term of large value to small one value.

4.3 Training Process

After normalized, training process will be start. By gathered all the data and train the data so that the network will go through learning processes and it will try to recognize input pattern. After that it will save the train process.

4.4 Testing Process

In this process, it will load save data in training process. After that, all the trained data will be compare with value from test data. The differences between actual data and predict data is called mean absolute error. By multiply with percentage, the value is said in term of mean absolute percentage error (MAPE). Temperature plays an important part in forecasting load and becoming as a reference. The result produce is in two terms; with and with temperature to see impact of temperature when doing load forecast.

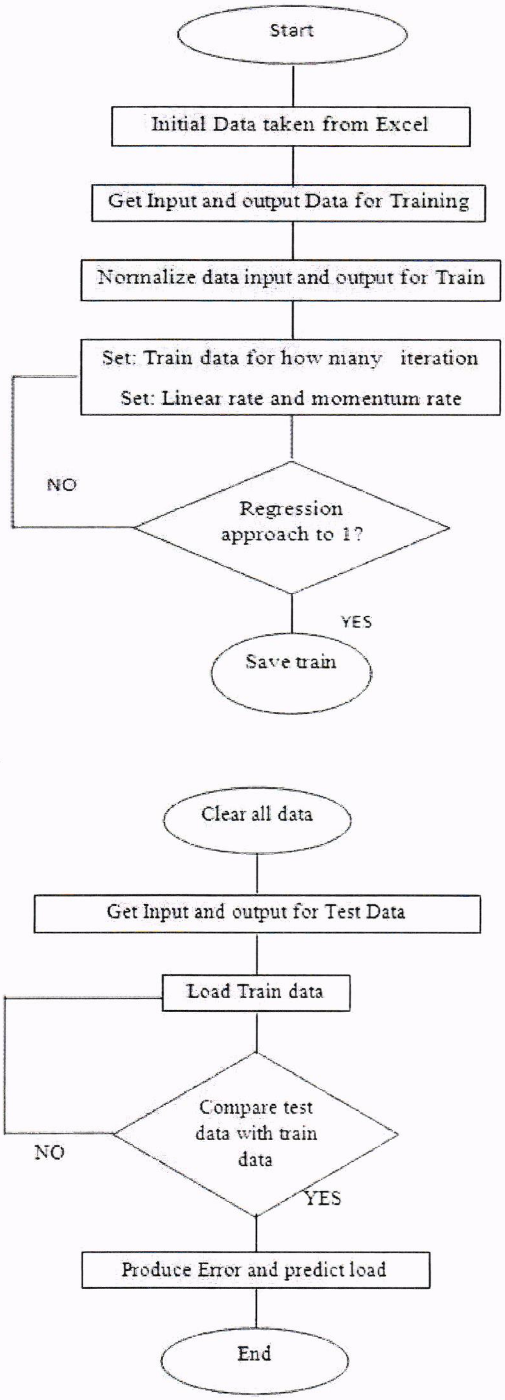

Figure 4: The flow chart of the programming

5.0 RESULT AND DISCUSSION

The developed of artificial neural network as a prediction technique for short term load forecasting. The train and test data can be divided into 2; with and without temperature. For weekdays approach, data involved is Monday, Tuesday, Wednesday, Thursday and Friday. All data has been tested with the same iteration.

Data load is taken from Tenaga Nasional Berhad, Jalan Bangsar and the temperature's data is taken from Jabatan Meteorologi, Jalan Barat, Petaling Jaya. The train data is taken from July 2008 until September 2008 for duration of 12 weeks. The test data is applied for year of 2009.

Result for Monday

Monday 10th August 2009 (With Temp)

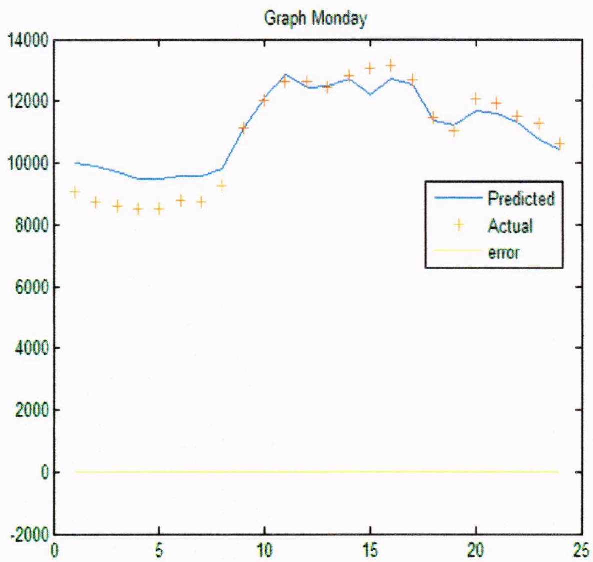

Figure 5: Normalize data

Figure 5 above shows that the actual and predict graph. The MAPE of this forecast is 3.3531%

Monday 10th August 2009 (Without Temp)

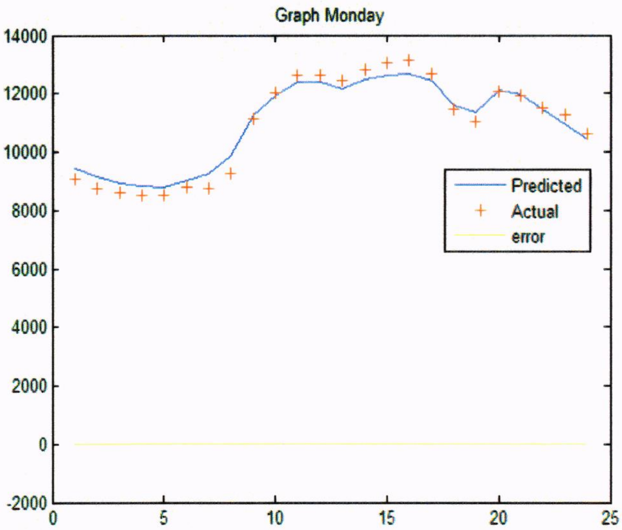

Figure 6: Normalize data

Figure 6 above shows that the actual and predict graph. The MAPE of this forecast is 1.7853%

Result for Tuesday

Tuesday 8th September 2009 (With Temp)

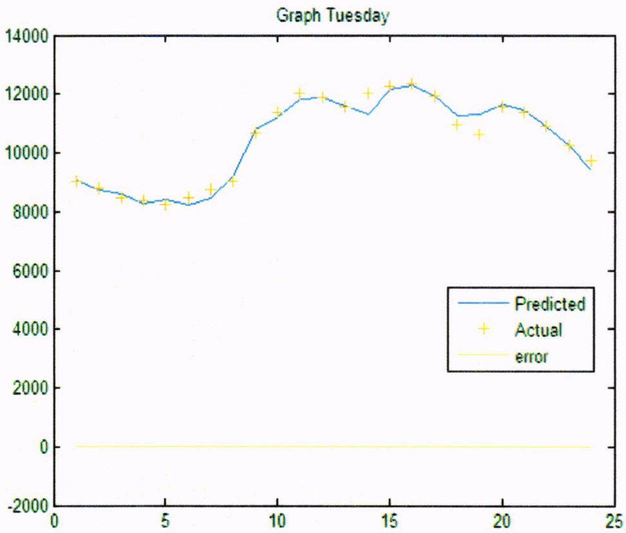

Figure 7: Normalize data

Figure 7 above shows that the actual and predict graph. The MAPE of this forecast is 1.7149%

Tuesday 8th Sept 2009 (Without Temp)

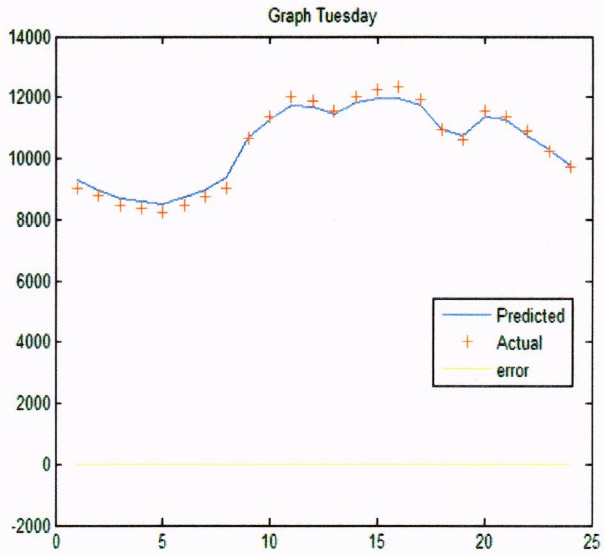

Figure 8: Normalize data

Figure 8 above shows that the actual and predict graph. The MAPE of this forecast is 1.9205%

Wednesday 26th August 2009 (Without Temp)

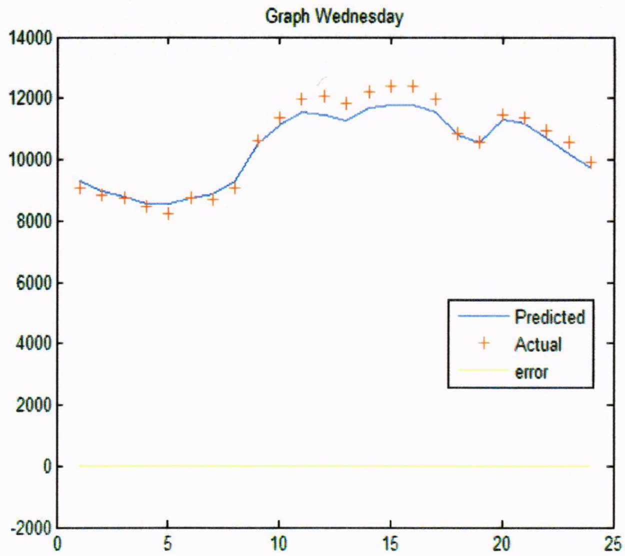

Figure 10: Normalize data

Figure 10 above shows that the actual and predict graph. The MAPE of this forecast is 0.4527%

Result for Wednesday

Wednesday 26th August 2009 (With Temp)

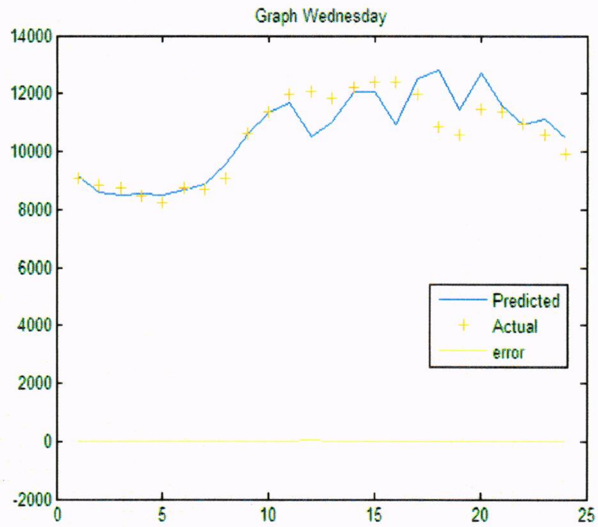

Figure 9: Normalize data

Figure 9 above shows that the actual and predict graph. The MAPE of this forecast is 3.4618%

Result for Thursday

Thursday 3rd Sept 2009 (With Temp)

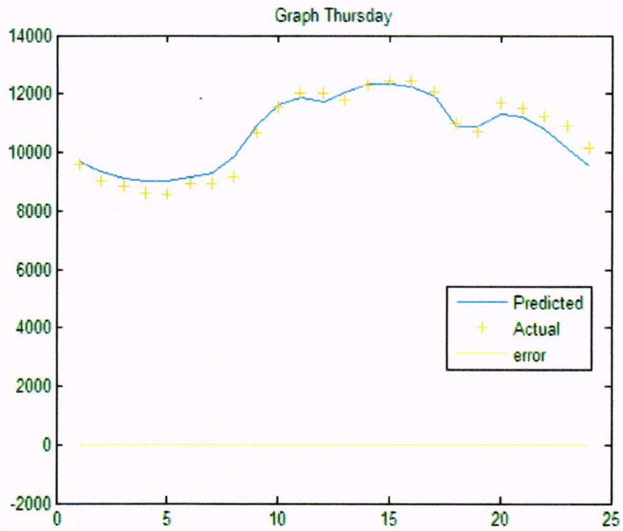

Figure 11: Normalize data

Figure 11 above shows that the actual and predict graph. The MAPE of this forecast is 4.1561%

Thursday 3rd Sept 2009 (Without Temp)

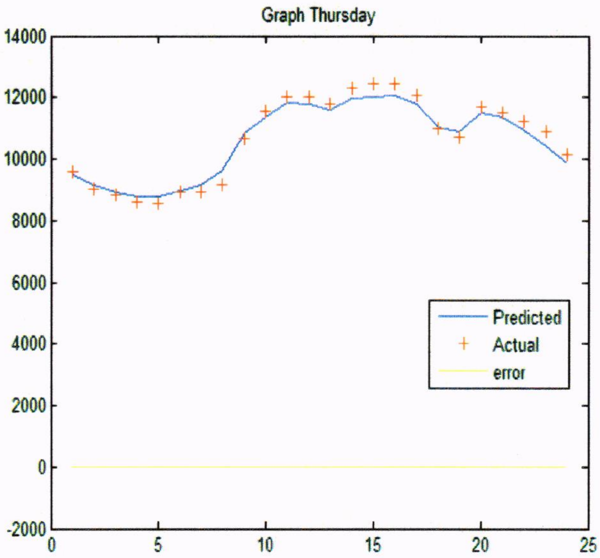

Figure 12: Normalize data

Figure 12 above shows that the actual and predict graph. The MAPE of this forecast is 1.1880%

Result for Friday

Friday 14th August 2009 (With Temp)

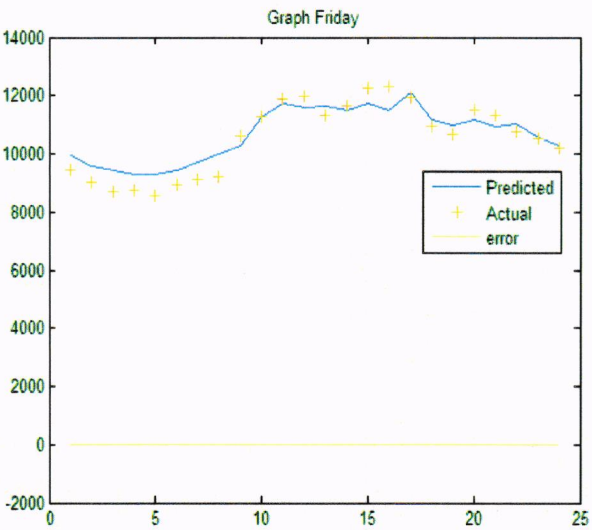

Figure 13: Normalize data

Figure 13 above shows that the actual and predict graph. The MAPE of this forecast is 3.3330%

Friday 14th August 2009 (Without Temp)

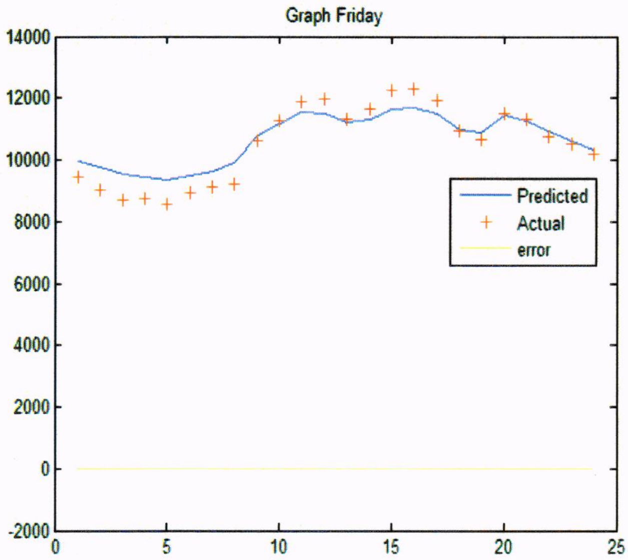

Figure 14: Normalize data

Figure 14 above shows that the actual and predict graph. The MAPE of this forecast is 3.1415%

Table 1: Load Forecasting Weekdays Results

Day	Without Temperature			With Temperature		
	Actual (MW/h)	Predict (MW/h)	MAPE (%)	Actual (MW/h)	Predict (MW/h)	MAPE (%)
Mon	10935.13	10946.25	1.7853	10935.13	10976.38	3.3531
Tue	10426.38	10432.45	1.7149	10426.38	10512.74	1.9205
Wed	10506.42	10343.73	0.4527	10506.42	10604.60	3.4618
Thu	10661.63	10681.43	1.1880	10661.63	10583.06	4.1561
Fri	10529.42	10659.55	3.1415	10529.42	10674.38	3.3330

In this project, in order to get the best mean absolute percentage error (MAPE), the load forecasting has been produced into two (2) categorize; with temperature and without temperature. The proposed of this two categorize is to see the impact of temperature to load forecasting. From the result above, the predicted load without temperature give the nearest value to the actual value of load usage compared to with temperature condition. Thus, the best mean absolute can be obtained by using result tested without temperature because it provide much more lower value of MAPE compared to with temperature value. In fact, as we can see the results in Table 1, temperature conditions really influence the load especially in Monday, 1.7853% without temperature and 3.3531% with temperature effect, Wednesday 0.4527% without temperature and

4.4618% with temperature effect and Thursday 1.1880% without temperature and 4.1561% with temperature effect. The reason for this phenomenon is the high penetration of electric space heaters or air conditioners, motors, lightings and others. Load forecasting is important for power system stability, contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market.

6.0 CONCLUSION

Load forecasting is very important to lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. As a conclusion, all objective in this final project has been achieved; to study about load forecasting and the influence of temperature develop by Artificial Neural Network (ANN) model by using MATLAB programming thus get the Mean Absolute Percentage Error (MAPE) below 5% in the forecasting load that has been provided by TNB Berhad. The basic concept of Artificial Neural Network model is a supervise learning that train network through learning algorithm and weight. Input with or without temperature will give effect to the prediction result of load forecasting in term of MAPE and since MAPE results are lower than 5%, this analysis is considered succeed.

7.0 RECOMMENDATION

The progress of ANN model to solve the STLF problem is a challenging problem and it should be investigated timely to improve the ANN model. The accuracy of the forecasts could be improved, if one would study these statistical models and develop mathematical theory that explains the convergence of these algorithms. Researchers should also investigate the boundaries of applicability of the developed models and algorithms. So far as I know, there is no single model or algorithm that is superior for all utilities. The reason is that utility service areas vary in differing mixtures of industrial, commercial, and residential customers. They also vary in geographic, climatologic, economic, and social characteristics. Besides nothing is known on a priori conditions that could detect which forecasting method is more suitable for a given load area. An important question is to investigate the sensitivity of the load forecasting algorithms and models to the number of customers, characteristics of the area, energy prices, and other factors such as humidity, wind speed, time factor and others. As mentioned in this analysis, temperature is an important factor that influences the load. The usual approach to short-term load forecasting uses the forecasted temperature scenario as an input. However, one of the most important recent developments in temperature forecasting is the so-called ensemble approach which consists of computing multiple forecasts. Then probability weights can be assigned to these ensembles.

8.0 ACKNOWLEDGEMENT

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Appendix A

Result for Monday 10th August 2009 (Without Temp)

Time	Actual	Predict	Error
100	9069	9445.45	4.1509
200	8755	9147.04	4.4779
300	8592	8929.63	3.9296
400	8481	8836.12	4.1871
500	8498	8800.75	3.5626
600	8805	9014.61	2.3806
700	8758	9272.74	5.8774
800	9271	9876.29	6.5289
900	11136	11255.68	1.0747
1000	11991	11906.67	0.7033
1100	12604	12403.69	1.5893
1200	12625	12381.27	1.9305
1300	12413	12140.36	2.1965
1400	12789	12499.30	2.2652
1500	13020	12604.25	3.1932
1600	13126	12685.11	3.3589
1700	12661	12422.71	1.8821
1800	11453	11602.26	1.3032
1900	11043	11355.27	2.8277
2000	12049	12082.71	0.2798
2100	11926	11948.26	0.1867
2200	11518	11465.42	0.4565
2300	11240	10944.32	2.6306
2400	10620	10409.98	1.9776
Total MAPE			1.7853

Result for Monday 10th August 2009 (With Temp)

Time	Temp	Actual	Predict	Error
100	24.3	9069	9531.021	5.0945
200	24.5	8755	9200.376	5.0871
300	24.5	8592	8874.959	3.2933
400	24.2	8481	8736.776	3.0158
500	24.4	8498	8855.598	4.2080
600	24.4	8805	8859.505	0.6190
700	24.8	8758	9030.209	3.1081
800	25.5	9271	9693.981	4.5624
900	26.6	11136	10951.24	1.6591
1000	28.0	11991	12332.98	2.8521
1100	28.1	12604	13095.33	3.8981
1200	27.8	12625	12360.91	2.0918
1300	28.0	12413	12367.95	0.3629
1400	29.0	12789	12664.48	0.9737
1500	30.1	13020	11866.28	8.8611
1600	28.1	13126	12649.07	3.6335
1700	26.4	12661	12539.78	0.9575
1800	25.3	11453	11924.54	4.1172
1900	25.1	11043	11456.71	3.7464
2000	24.8	12049	11980.62	0.5675
2100	24.8	11926	11717.31	1.7499
2200	24.7	11518	11178.68	2.9459
2300	24.4	11240	10673.28	5.0418
2400	24.4	10620	10171.42	4.2239
Total MAPE				3.3531

Appendix B

Result Tuesday 8th Sept 2009 (Without Temperature)

Time	Actual	Predict	Error
100	8997	9286.606	3.2189
200	8780	8971.648	2.1828
300	8453	8708.085	3.0177
400	8342	8604.006	3.1408
500	8200	8505.796	3.7292
600	8456	8753.754	3.5212
700	8729	8948.097	2.5100
800	9011	9389.397	4.1993
900	10654	10686.52	0.3053
1000	11378	11257.24	1.0613
1100	12002	11742.64	2.1610
1200	11865	11706.99	1.3317
1300	11538	11433.19	0.9084
1400	12027	11805.63	1.8406
1500	12226	11943.49	2.3107
1600	12348	11973.56	3.0324
1700	11929	11733.04	1.6427
1800	10914	10936.92	0.2100
1900	10624	10732.48	1.0211
2000	11550	11375.42	1.5115
2100	11361	11254.38	0.9385
2200	10901	10754.24	1.3463
2300	10237	10270.71	0.3293
2400	9711	9784.884	0.7608
Total MAPE			1.9205

Result Tuesday 8th Sept 2009 (With Temperature)

Time	Temp	Actual	Predict	Error
100	23.9	8997	8808.297	2.0974
200	23.9	8780	8765.03	0.1705
300	24.0	8453	8745.073	3.4553
400	23.8	8342	8565.219	2.6759
500	24.0	8200	8378.572	2.1778
600	23.7	8456	8401.903	0.6398
700	23.8	8729	8680.526	0.5553
800	25.3	9011	9464.279	5.0303
900	26.3	10654	10387.91	2.4976
1000	28.5	11378	11234.85	1.2582
1100	29.4	12002	11863.05	1.1577
1200	29.6	11865	11895.09	0.2536
1300	30.1	11538	11650.28	0.9732
1400	31.4	12027	11822.01	1.7044
1500	24.3	12226	12835.88	4.9884
1600	24.3	12348	12876.75	4.2821
1700	24.5	11929	12191.37	2.1994
1800	25.4	10914	11329.22	3.8044
1900	24.9	10624	11341.61	6.7546
2000	25.2	11550	11495.38	0.4729
2100	25.2	11361	11337.36	0.2081
2200	25.4	10901	10732.1	1.5494
2300	25.2	10237	9942.823	2.8737
2400	24.9	9711	9561.226	1.5423
Total MAPE				1.7149

Appendix C

Wednesday 26th August 2009 (Without Temp)

Time	Actual	Predict	Error
100	9,055	9292.03	2.6177
200	8,823	8975.32	1.7265
300	8,737	8767.13	0.3449
400	**8,465**	8554.84	1.0614
500	8,224	8556.46	4.0427
600	8,722	8729.38	0.0847
700	8,667	8862.28	2.2532
800	9,077	9306.31	2.5263
900	10,619	10536.23	0.7794
1000	11,340	11100.01	2.1163
1100	**11,949**	11565.24	3.2116
1200	12,073	11473.55	4.9652
1300	11,839	11271.02	4.7975
1400	12,222	11661.21	4.5883
1500	12,385	11763.27	5.0200
1600	**12,384**	11783.26	4.8509
1700	11,977	11530.32	3.7295
1800	10,839	10815.11	0.2203
1900	10,544	10581.05	0.3514
2000	**11,449**	11319.15	1.1341
2100	11,337	11161.72	1.5460
2200	10,949	10724.48	2.0505
2300	10,574	10199.09	3.5455
2400	9,904	9720.99	1.8478
Total MAPE			0.4527

Wednesday 26th August 2009 (With Temp)

Time	Temp	Actual	Predict	Error
100	23.9	9,055	9153.59	1.0889
200	23.6	8,823	8618.41	2.3187
300	23.5	8,737	8487.56	2.8549
400	23.8	**8,465**	8553.63	1.0471
500	23.5	8,224	8525.76	3.6694
600	23.9	8,722	8698.08	0.2742
700	23.9	8,667	8880.39	2.4622
800	24.4	9,077	9591.92	5.6729
900	25.3	10,619	10611.05	0.0748
1000	26.3	11,340	11379.28	0.3464
1100	27.8	**11,949**	11696.70	2.1115
1200	29.2	12,073	10526.09	2.8129
1300	29.3	11,839	11030.78	6.8267
1400	28.9	12,222	12051.38	1.3959
1500	28.8	12,385	12073.59	2.5143
1600	29.3	**12,384**	10936.10	11.6917
1700	29.6	11,977	12538.08	4.6847
1800	28.7	10,839	12818.35	1.2614
1900	27.8	10,544	11446.34	8.5579
2000	27.4	**11,449**	12732.00	11.2063
2100	26.8	11,337	11606.51	2.3773
2200	26.3	10,949	10954.93	0.0542
2300	26.2	10,574	11122.19	5.1844
2400	25.9	9,904	10477.86	5.7943
Total MAPE				3.4618

Appendix D

Result Thursday 3rd Sept 2009 (Without Temperature)

Time	Actual	Predict	Error
100	9594	9472.62	1.2652
200	9019	9169.94	1.6736
300	8828	8934.64	1.2079
400	8618	8787.94	1.9719
500	8536	8770.21	2.7437
600	8910	8963.78	0.6036
700	8926	9142.10	2.4211
800	9160	9608.66	4.8980
900	10653	10837.30	1.7300
1000	11558	11351.22	1.7890
1100	11997	11838.75	1.3191
1200	12033	11799.21	1.9429
1300	11774	11576.21	1.6799
1400	12274	11944.53	2.6843
1500	12411	12022.80	3.1279
1600	12437	12037.82	3.2096
1700	12076	11777.30	2.4735
1800	10989	11048.88	0.5449
1900	10680	10866.17	1.7431
2000	11676	11517.91	1.3539
2100	11492	11367.23	1.0857
2200	11220	10915.73	2.7119
2300	10881	10404.42	4.3799
2400	10137	9838.12	2.9484
Total MAPE			1.1880

Result Thursday 3rd Sept 2009 (With Temperature)

Time	Temp	Actual	Predict	Error
100	25.7	9594	9662.416	0.7131
200	25.5	9019	9353.049	3.7038
300	25.2	8828	9122.481	3.3358
400	25.0	8618	9023.304	4.7031
500	24.9	8536	9038.699	5.8892
600	25.0	8910	9163.834	2.8489
700	25.0	8926	9301.529	4.2071
800	25.9	9160	9842.904	7.4553
900	27.4	10653	10947.12	2.7609
1000	28.8	11558	11655.44	0.8430
1100	29.4	11997	11849.52	1.2293
1200	31.2	12033	11741.63	2.4214
1300	31.5	11774	12071.13	2.5237
1400	31.8	12274	12330.22	0.4580
1500	32.1	12411	12337.6	0.5914
1600	29.9	12437	12244.54	1.5475
1700	24.8	12076	11906.39	1.4046
1800	22.1	10989	10896.16	0.8449
1900	22.3	10680	10901.37	2.0727
2000	22.5	11676	11304.02	3.1859
2100	23.1	11492	11199.21	2.5478
2200	23.5	11220	10787.35	3.8561
2300	23.7	10881	10145.48	6.7597
2400	23.8	10137	9528.866	5.9992
.Total MAPE				4.1561

Appendix E

Friday 14th August 2009 (Without Temp)

Time	Actual	Predict	Error
100	9,451	9937.54	5.1481
200	9,039	9743.88	7.7983
300	8,713	9541.54	9.5093
400	**8,727**	9425.84	8.0079
500	8,538	9364.09	9.6755
600	8,922	9497.41	6.4494
700	9,133	9612.41	5.2492
800	9,185	9917.21	7.9718
900	10,627	10778.22	1.4230
1000	11,253	11184.57	0.6080
1100	**11,874**	11524.95	2.9396
1200	11,949	11518.33	3.6042
1300	11,329	11237.38	0.8087
1400	11,660	11307.16	3.0260
1500	12,237	11625.35	4.9983
1600	**12,290**	11662.44	5.1062
1700	11,940	11499.79	3.6868
1800	10,944	10969.44	0.2325
1900	10,643	10884.38	2.2680
2000	**11,499**	11432.24	0.5806
2100	11,289	11277.61	0.1009
2200	10,767	10921.30	1.4331
2300	10,528	10631.19	0.9802
2400	10,169	10334.84	1.6309
Total MAPE			3.1415

Friday 14th August 2009 (With Temp)

Time	Temp	Actual	Predict	Error
100	26.6	9,451	9945.387	5.2311
200	25.4	9,039	9593.799	6.1378
300	25.5	8,713	9459.086	8.5629
400	24.9	**8,727**	9309.957	6.6799
500	24.1	8,538	9289.093	8.7971
600	24.3	8,922	9443.744	5.8478
700	24.5	9,133	9723.724	6.4680
800	25.6	9,185	10008.14	8.9619
900	27.7	10,627	10261.40	3.4402
1000	28.9	11,253	11254.04	0.0093
1100	30.0	**11,874**	11731.36	1.2012
1200	31.1	11,949	11589.56	3.0081
1300	32.5	11,329	11650.72	2.8399
1400	32.3	11,660	11503.48	1.3423
1500	31.9	12,237	11734.94	4.1028
1600	31.3	**12,290**	11507.43	6.3675
1700	24.3	11,940	12100.32	1.3428
1800	24.3	10,944	11147.92	1.8633
1900	24.9	10,643	10985.78	3.2208
2000	25.0	**11,499**	11151.74	3.0199
2100	24.9	11,289	10942.64	3.0680
2200	25.0	10,767	11031.48	2.4565
2300	24.9	10,528	10539.40	0.1084
2400	24.8	10,169	10279.68	1.0885
Total MAPE				3.3330