



UNIVERSITI PUTRA MALAYSIA

***MODELING REGIONAL PEAK LOAD FORECASTING USING DYNAMIC
NARX NEURAL NETWORK WITH TEMPERATURE***

FARIDAH BINTI BASARUDDIN

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**MODELING REGIONAL PEAK LOAD FORECASTING USING DYNAMIC
NARX NEURAL NETWORK WITH TEMPERATURE**

By

FARIDAH BINTI BASARUDDIN

**Thesis Submitted to the School of Graduate Studies, University Putra Malaysia, in
Fulfillment of the Requirements for the Degree of Doctor of Philosophy**

August 2014

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Abstract of thesis presented to the Senate of University Putra Malaysia in Fulfillment of the requirement for the Degree of Doctor of Philosophy

MODELING REGIONAL PEAK LOAD FORECASTING USING DYNAMIC NARX NEURAL NETWORK WITH TEMPERATURE

By

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August 2014

Chairman: Rosnah Mohd Yusuff, PhD

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Temperature is one of the most significant weather parameters affecting load consumption. Temperature varies according to demographic region and could not be incorporated in the Malaysia load forecasting as the latter emphasized a general style of aggregate forecasting that predicts the load consumption for the whole of the country. Such load forecasting results would not be able to identify where the power load takes place and also is not helpful for power facilities construction location planning. Therefore the models are inadequate to predict the control of load in critical situations such as during drought or monsoon seasons that occur at certain time of the year or occasionally when weather is unpredicted. Hence it is of interest to implement a model that serves the above purposes as well as to improve on the supply of load.

A regional peak hourly load forecasting at selected meteorological stations in Malaysia using Dynamic Narx Neural Network Model is implemented. The advanced dynamic Narx neural network model (NARXNET) without and with temperature is applied to peak hourly load forecasts at selected meteorological stations in Malaysia. The performances of both models are compared with time series, Auto Regressive Integrated Moving Average (ARIMA), ARIMA transfer function with temperature model and another neural network, Focused Time Delay (FTDNN) model in terms of parameters investigations and models' performances. NARXNET forecasts for the week ahead peak hourly load achieved Mean Absolute Percentage Error (MAPE) ranging from 0.3422 to 0.9066 while the five hundreds -hours ahead peak hourly load at the stations with MAPE 0.0109 to 0.1733. NARXNET with temperature model forecasts for the week ahead peak hourly load produced MAPE ranging from 0.2773 to 0.6533 and the five hundreds -hours ahead peak hourly load forecasts gave MAPE ranging from 0.0248 to 0.1391. NARXNET with temperature model is able to capture the effect of temperature on the peak hourly load system at three out of five stations.

ARIMA and ARIMA transfer function with temperature, for the five hundreds - hours ahead peak hourly load forecasts, however gave MAPE that ranged from 2.700 to 5.390 and 2.702 to 5.393 respectively. The effect of temperature using ARIMA transfer function

is captured only at two out of five stations and the improvement in the forecast is very small.

The experimental results have shown that NARXNET with temperature model due to the existence of feedback connection where the outputs are regressed to the network is capable of improving the forecasting performance through the effect of temperature. Being part of neural network, NARXNET is seen as a promising black box model in identifying a nonlinear system without/with prior knowledge. Thus Narxnet can be used for real time simulations. The simulation results proved that NARXNET, having the ability dealing with nonlinear data outperformed ARIMA and ARIMA Transfer function models. The excellence performance of NARXNET in dynamical modeling was supported by studies conducted by Lin et al.(1997), Luo and Puthusserypady (2006), Nordin (2009) and others.

As both historical temperature and load data were applied to the NARXNET model, this research also considered some aspect of regression analysis involving load and weather parameters with more emphasis on temperature-load relationship. The historical peak hourly load and temperature data for a period of one year were applied to both models, NARXNET and regression. The trend of the peak hourly load consumption for a selected week and load profile on a selected day within the study period were analyzed. The analysis provides better understanding on the characteristics of Malaysian power load system.

The implementation of the model was validated by comparing with other existing works. Both the validation and simulation results were similar. It can be concluded that NARXNET with temperature model performed better than other models that use temperature and thus by applying NARXNET model to predict the electricity consumption at locations that are affected by extreme changes in temperature, the problem of over production or under production of electricity that in turn influence the sustainable development of the economy could be overcome.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk Ijazah Doktor Falsafah

**PEMODELAN RAMALAN BEBAN PUNCAK MENGIKUT RANTAU
MENGUNAKAN RANGKAIAN NEURAL DINAMIK NARX DENGAN SUHU**

Oleh

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Suhu merupakan salah satu parameter cuaca yang ketara mempengaruhi penggunaan elektrik. Suhu berbeza mengikut kedudukan atau rantau dan tidak dapat di aplikasi di dalam membuat ramalan kadar penggunaan elektrik di Malaysia yang secara umum menekankan ramalan beban elektrik agregat di mana ramalan penggunaan beban elektik di buat untuk seluruh negara. Oleh itu ramalan kadar penggunaan elektrik yang dihasilkan bukan saja tidak dapat mengenal pasti jumlah penggunaan elektik di kawasan-kawasan tertentu malahan tidak dapat membantu di dalam merancang pembinaan kemudahan dan infrastruktur penjanaan elektrik mengikut keperluan kawasan-kawasan tersebut. Oleh itu model-model yang sedia ada tidak sesuai dan tidak tepat dalam membuat ramalan penggunaan elektrik terutamanya di saat genting apabila terdapat musim panas atau musim tengkujuh yang berpanjangan dan keadaan cuaca yang tidak menentu dan sukar di ramal. Sehubungan itu adalah menjadi satu keutamaan atau kepentingan bagi penyelidik dalam bidang ramalan penggunaan elektrik untuk mengaplikasi satu model yang bukan saja dapat mengatasi masalah yang tertera di atas, malahan dapat meningkat dan memperbaiki sistem pembekalan elektrik secara keseluruhan.

Satu pendekatan dalam membuat ramalan berhubung kadar penggunaan electric maksima bagi sesebuah kawasan (rantau) di beberapa stesen kaji cuaca di Malaysia mengguna model dinamik NARXNET telah dicadang. Model dinamik lanjutan NARXNET yang dicadangkan samada dengan gabungan suhu atau tidak telah diaplikasikan dalam membuat ramalan penggunaan maksima beban elektrik mengikut jam di stesen-stesen kajicuaca yang dipilih. Prestasi model NARXNET samada dengan gabungan suhu atau tidak dalam membuat ramalan penggunaan maksima beban elektrik mengikut jam telah dibanding dengan model 'time series', 'Auto Regressive Integrated Moving Average' (ARIMA), 'ARIMA transfer' dengan gabungan suhu dan satu lagi rangkaian model neural, 'Focused Time Delay' (FTDNN) dari segi ketepatan dalam penggunaan parameter beban elektrik dan suhu serta pengesahan prestasi dan kelebihan model NARXNET tersebut. Model NARXNET tanpa gabungan suhu memberi ramalan penggunaan beban maksima elektrik mengikut jam bagi satu minggu ke hadapan di stesen-stesen kajian

dengan nilai ralat 'MAPE' di antara 0.3422 hingga 0.9066 manakala bagi ramalan 500 jam ke hadapan dengan nilai 'MAPE' di antara 0.0109 hingga 0.1733. Model NARXNET dengan gabungan suhu pula bagi ramalan mengikut jam untuk satu minggu ke hadapan menghasilkan nilai ralat 'MAPE' di antara 0.2773 hingga 0.6533 dan ramalan bagi 500 jam ke hadapan menghasilkan nilai ralat 'MAPE' di antara 0.0248 hingga 0.1391

Model NARXNET dengan gabungan suhu berupaya mengesan pengaruh suhu terhadap ramalan penggunaan suhu maksima mengikut jam di tiga daripada lima stesen. Model ARIMA and ARIMA 'transfer function', menghasilkan nilai 'MAPE' diantara 2.700 sehingga 5.390 dan 2.702 sehingga 5.393. Pengaruh suhu hanya dikesan di dua dari lima buah stesen dan peningkatan di dalam ramalan penggunaan maksima beban elektrik mengikut jam sangat kecil.

Keputusan dari ujikaji atau percubaan yang dilakukan sepanjang penyelidikan ini telah membuktikan bahawa model NARXNET dengan gabungan suhu yang mempunyai saluran yang menghubungkan semula 'output' dan 'input' di mana 'output' dimasukkan semula ke dalam 'network' dapat mempertingkatkan prestasi ramalan yang dihasilkan dari kesan pengaruh suhu. Model NARXNET yang merupakan sebahagian dari rangkaian neural dianggap sebagai sebuah model kotak hitam yang semakin menonjol penggunaannya dalam mengenal pasti sistem yang bukan linear berdasarkan pengetahuan sedia ada atau tiada, disamping dapat di aplikasi untuk tujuan simulasi yang nyata. Prestasi dan keupayaan model NARXNET dalam mengendali data yang tidak linear adalah lebih baik dari model ARIMA dan 'ARIMA transfer function'. Pencapaian cemerlang yang ditunjukkan oleh model NARXNET dalam Permodelan dinamik disokong oleh kajian-kajian yang telah dijalankan oleh Lin dan rakan-rakan (1997), Luo dan Puthusserypady (2006), Nordin (2009) dan lain-lain.

Kedua-dua data terdahulu bagi suhu dan beban elektrik yang digunapakai bagi mengaplikasikan model NARXNET juga di guna dalam analisis regresi yang melibatkan beban elektrik dan unsur-unsur cuaca terutamanya suhu. Data setiap jam penggunaan beban elektrik dan data suhu mengikut jam diguna dalam model NARXNET gabungan suhu dan regresi. Aliran penggunaan mingguan beban elektrik maksima dan profil beban elektrik untuk hari tertentu dalam jangka masa dimana penyelidikan dijalankan telah dianalisa. Hasil dari analisis yang dibuat memberi gambaran yang lebih jelas bagi kita memahami ciri-ciri sistem kuasa elektrik di Malaysia.

Bagi mengenal pasti kesahihan model yang telah diaplikasi, penyelidikan ini telah membandingkannya dengan model-model yang sedia ada. Keputusan perbandingan dan simulasi adalah serupa. Oleh itu bolehlah disimpulkan bahawa model NARXNET dengan gabungan suhu merupakan satu model yang lebih baik dari model-model gabungan suhu bandingan dan harapan kami model ini dapat diaplikasikan dalam membuat ramalan penggunaan maksima beban elektrik di kawasan di mana pengaruh suhu amat ketara agar masalah penjanaan kuasa elektrik yang kurang atau berlebihan dapat diatasi dan seterusnya dapat membantu dan mengekal pembangunan ekonomi negara.

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I certify that a Thesis Examination Committee has met on 21 August 2014 to conduct the final examination of Faridah binti Basaruddin on her thesis entitled “Modeling Regional Peak Load Forecasting Using Narx Neural Network With Temperature” in accordance with the Universities and University College Act 1971 and the Constitution of the University Putra Malaysia [P. U. (A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligent
ANN	Artificial Neural Network
AR	Auto Regressive
ARCH	Auto Regressive Conditional Heteroskedasticity
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
ARMAX	Auto Regressive Moving Average With Extraneous
ART	Adaptive Resonance Theory
BJ	Box Jenkins
BNN	Baysian Neural Network
BP	Backward Propagation
EGARCH	Engle General Autoregressive Heteroskedasticity
EGARCH-GED	Engle General Autoregressive Heteroskedasticity with Generalized Error Distribution
ES	Expert System
ESM	Exponential Smoothing
ESTAR GARCH	Exponential Smooth Transition and Autoregressive General Autoregressive Heteroskedasticity
FI	Fuzzy Inference
FTDNN	Focused Time delay Neural Network
GA	Genetic Algorithm
GARCH	General Autoregressive Heteroskedasticity
GF	Grey Forecasting
HHT	Hilbert-Huang Transform
ITSM	Integrated Time Series Modeling
KF	Kalman Filter
LS-SVM	Least squares support vector machine
LSTAR-GARCH	Logistic Smooth Transition Auto-Regressive
MA	Moving Average
MAPE	Mean Absolute Percentage Error
MATLAB	MATrix LABoratory
MP	Multilayer Perceptron
MSPE	Mean Square Percentage Error
NN	Neural network
NARXNET	Nonlinear AutoRegressive with eXogenous inputs Network
PARCH	Power Autoregressive Conditional Heteroskedasticity
PARCH-GED	Power Autoregressive Conditional Heteroskedasticity with Generalized Error Distribution
PE	Percentage Error
PSO	Particle Swamp Optimization
RME	Ratio of Medians Estimator
RMSE	Root Mean Square Error

SA	Simulated Annealing
SARIMA	Seasonal autoregressive integrated moving average
SARIMAX	Seasonal autoregressive integrated moving average with extraneous
S-ESM	Seasonal Exponential Smoothing
SOM	Self Organized Map
SOFNN	Self-organizing fuzzy neural network
SPSS	Statistical Package for Social Science
STAR	Smooth Transition Autoregressive
SVM	Support Vector Machine
SVR	Support Vector Regression
TARCH	Threshold Autoregressive Conditional Heteroskedasticity
TCGARCH	Threshold Component General Autoregressive Heteroskedasticity
TGARCH	Threshold General Autoregressive Heteroskedasticity
TGARCH-GED	Threshold General Autoregressive Heteroskedasticity with generalized error distribution
TNB	Tenaga Nasional Berhad
WM	Wang–Mendel

CHAPTER ONE

INTRODUCTION

1.1 Research Background

The power industry in Malaysia had undergone a tremendous development during the last few decades. The growing demands by the consumers and stakeholders for a reliable supply of electricity at a reasonable cost and for an efficient planning, operation and dispatch of the power system respectively have increased the necessity of having a robust and accurate load forecasting. The largest power utility company whose core activities are in generation, transmission and distribution of electricity serves an estimated 8.3 million customers in Peninsular Malaysia, Sabah and Labuan (Tenaga Nasional Berhad, 2013). Six thermal stations and three major hydroelectric schemes generate and supply electricity to households and industries in Peninsular Malaysia (Tenaga Nasional Berhad, 2013).

The electricity consumption in Malaysia has been steadily increased in the past decade and is expected to increase by 3.1% from 2012 until 2020 due to strong demands from the industrial and residential sectors (Kui, 2012).

Electricity next to water and food is one of the most crucial needs to human beings. It is considered as a sustainable resource that simplifies our lives. Unlike physical goods or other energy sources, electricity cannot be stored, it responds to demand and requires some lead time. It is produced at the time of use and does not lend itself easily to storage. Thus the matching of supply to demand is of utmost important to maintain the level of reliable supply that is expected in today's society. Due to this reason, the forecasting of electricity demand has become one of the major research fields in engineering and applied sciences and has received much attention over the last ten years. There is an increasing number of articles pertaining to load forecasts that have been published in scientific journals each year and they draw the attention of the researchers in this area to apply, improve and come out with models that suit their specific forecasting needs.

Different forecasters and researchers have attempted various load forecasting models to predict the short term maximum load consumption of Malaysia. These include the studies conducted by Othman et al. (2009), Harun et al. (2009), Ismail et al. (2008), Ismail and Jamaluddin (2007), Rahman (2005), Razak et al. (2008) and (2010), Nagi et al. (2007) and Kamel and Baharudin (2007). Their contributions enabled us to understand the load forecasting scenario in Malaysia and further enhanced the interest in this area.

1.1.1 Problem Statement

There is no regional peak load forecasting currently in Malaysia using Narx neural network with temperature. All the forecasting models that were established predict the load, either average or peak load for the whole of Malaysia with few that focused on specific regions. In this doctoral research a regional load forecasting models at selected meteorological stations were constructed using several models and comparison of all models were made in order to come out with the best model for the above purpose. It is

very important to have a regional load forecasting as the weather parameters vary according to demographic locations. Even though several of weather parameters do not seemed to have significant contribution towards the load forecasting but temperature has been shown to have major effects on load consumption at most places on the world. Temperature has been proven by the earlier studies to have great impact on load consumption.

A simulation of a 2°F increase in temperature for July and August 2000 resulted in a 4.6% increase in electricity demand for the Pennsylvania-New Jersey-Maryland (PJM) region as a whole. These being the peak cooling demand months where the average increase over the year would likely be somewhat lower. Results that are similar in magnitude were reported for a simulation of electricity demand in California by Baxter and Calandri (1992), who found that there was a 3.8% increase over the year for a similar warming scenario (Crowley and Joutz, 2005).

The influence of temperature and its accumulation for load works when the temperature is high. How high could the load be? Research shows that the relationship of temperature and load is positive correlation when the average temperature is higher than 20°C (Genyong and Jingtian, 2009).

The national power utility company in Malaysia has applied three common methods of load forecast, the standard multiple linear regression, moving average and exponential smoothing for daily and half hourly load. These techniques, however have limitations to predict load successfully when dealing with real time weather inputs from the meteorological department (Yang, 2006).

Thus, having regional load forecast model with temperature will enable the smooth load distribution and hence reduce the power shortage or blackout throughout the region. In case there is any opening of new township or expansion of the existing township, the model could easily be corporated with the adjustment and increase in the load consumption. Both time series and neural network models are compared in this research in implementing more accurate forecasts.

1.1.2 Research Problems

Mathematical modeling of power load in Malaysia is currently independent of weather elements. Therefore the models are inadequate to predict the amount of electricity that should be generated to supply special groups of consumers over a specific period and location that was affected by weather parameters. Hence it is of interest to develop a model that serves the above purposes as well as to improve on the supply of load. Variety of techniques such as short term, moderate term and long term forecasting and approaches such as time series, linear and non linear regression and neural network have been proposed and applied in this area to improve the quality of forecasting accuracy, making the operation at least cost and maintaining an acceptable reliability (Kung et al., 1998).

Besides weather parameters, factors such as long term variation which is due to factors such as population growth, economic development and consumers' awareness on electricity consumption conservations will also affect the load consumption especially in long term load forecasting. Short term load forecasting or power load forecasting of

several hours ahead to a week ahead is essential in electric power system operation and planning. To enable an accurate forecasting, the effects of all influencing factors such as weather information, time of the day and special days and holidays should be considered and included in the forecasting process. In Malaysia, the effects of four moving holidays representing religious and cultural celebrations , Aidil Fitri, Aidil Adha, Chinese New Year and Deepavali lead to inaccurate load forecasting (Razak, 2013).

The accuracy of short-term load forecasts can have significant effects on power system operations, as the economy of operation and the control of the power system may be quite sensitive to forecasting errors. Significant forecasting errors can lead to either overly conservative or overly risky scheduling, which can in turn induce heavy economic penalties. Forecasts that are too high may result in the start-up of too many units and unnecessarily high levels of reserves. On the other hand, forecasts that are too low may result in failure to provide the necessary spinning and operating reserve required by power pool agreements. In both cases, forecasts errors could result in increased operating costs (Papalexopoulos and Hesterberg, 1990). Further study on the impact of weather parameters like humidity, precipitation, wind-speed/velocity on load forecasting is needed as short-term load forecasting is mainly affected by weather parameters.

In general the style of load forecast in Malaysia as in other countries in the world, emphasized aggregate load forecasting. Such load forecasting could not incorporate temperature as the later varies according to locations and the results not only cannot identify where the power load takes place but also is not helpful for power facilities construction location planning.

Regional load forecasting instead involves predicting the amount of electricity that should be generated to supply specific kinds of consumers over a specific period and location. It is explicitly intended for applications in generation capacity installation, long term capital investment, electricity price setting and transmission capacity expansion in different regions (Hsu and Chen, 2003).

In an age of spiraling of oil and coal prices with rapid urban and rural industrialization revealed the futile hope for a cheap and reliable electricity supply. Regional load forecast that incorporates temperature could no longer be ignored in Malaysia. However, such regional load forecasting is still lacking in Malaysia.

1.2 Research Objectives

1.2.1 General Objective

The ultimate objective of the study is to implement an hourly regional temperature sensitive peak load demand model by comparing both statistical time series and neural network techniques. The main focus is on the significant effect of temperature on the electrical load consumption.

1.2.2 Specific Objectives

The specific objectives are as follows:

- i) To determine the effects of temperature on load consumption in Malaysia.
- ii) To select the most accurate model that is able to capture the effect of temperature for the regional peak hourly load forecasts in Malaysia.
- iii) To implement the model for the regional peak hourly load forecasts in Malaysia.

1.3 Research Scope

Hypothesis related to the study objectives are as follows:

- i) In implementing time series Auto Regressive Integrated Moving Average (ARIMA) model for the peak hourly load forecasting, it is hypothesized that the peak load demand will be totally dependent on the weather parameters especially the temperature. Other weather parameters might have slight impact on the load demand.
- ii) ARIMA transfer function with temperature model is implemented to determine the effect of temperature on the peak hourly load consumption.
- iii) The Dynamic Narx with temperature model is hypothesized to be more efficient in forecasting load demand especially on days when there is sudden change in the weather condition and in terms of computing time.
- iv) Time series (linear) and Neural Network (nonlinear) models without/with temperature are to be implemented and compared using real data obtained from the power utility company.
- v) The temperature sensitive regional peak hourly load forecasting model provides more accurate results for forecasting peak hourly load demand in Malaysia.

The research focuses mainly on short term load forecast (STLF). The STLF is the prediction of load that varies from an hour to a week. Eventhough the load data obtained through online system was in ten minutes interval, the data was reduced to hourly data to be accommodated into the model. The peak hourly load data from eight stations for a period of three years comprising of all sectors, industrial, commercial and residential from 1st January 2006 to 31st December 2008 were used in the research. However only an hourly weather data including temperature at 5 stations from 1st January until 31st December 2006 were applied to the model. Statistical time series techniques are developed as comparison due to their users friendly algorithm accessibility and they allow better understanding of the problem through explicit models equations and justified significance testings.

1.4 Thesis Organization

The thesis is organized into 5 chapters:

Chapter 1 states the background, the problems, the objectives and the scope of the research. Chapter 2 reviews a number of previous and current published research techniques on statistical time series and neural network methods pertinent to the short

and medium term load forecasting. The strength and the weakness on the implementation of each technique is discussed to identify the gap in load forecasting. Common problems in current practice of load forecasting are laid out and the possibilities of applying the implemented method in regional peak hourly load forecasting with temperature would reduce the problems and thus improved the forecasting results. Chapter 3 discusses on the implementation of time series ARIMA, ARIMA transfer function with temperature, regression models and neural network, Focused Time Delay Neural Network (FTDNN) and Narx without/ with temperature models. All the steps involved in the implementation of each model are summarized in the form of flowcharts.

The first part of this chapter focuses on the implementation of time series ARIMA model using small data values and large data values. The methodology for each time series model includes the phases of model identification and selection, the parameter transformation and estimation, and model application. The requirements of forecasting accuracy criteria, diagnostic plots and statistical tests are essential in the selection of best fit model.

The models with small data values were executed using integrated time series modeling (ITSM) soft ware that employed the first 250 peak hourly load data of the year 2006. The peak hourly load data from all the five stations were separately applied to the models and the hour ahead peak load , the next day peak hourly load and the next week peak hourly load forecasts are calculated and analysed based on the fitted time series ARIMA models. Large data values consist of peak hourly load data for the year 2006 that are applied and executed through the time series SPSS packages and similar peak hourly load forecasts were performed and the forecasting errors were calculated.

The second part of the chapter concentrates on the linear regression analysis of load with respect to temperature and other weather parameters respectively. The correlation between load as dependent variable and weather parameters as independent variables are established. The correlation coefficient that measures the strength of the relationship between the variables are calculated and the equation of the best fitting line is derived.

The third part is the implemetation of ARIMA transfer function with temperature model where the peak hourly load and temperature are applied and executed using program from SPSS packages.

The fourth part of this chapter presents the implementation of FTDNN and NARXNET models through training and testing of neural networks. Different iteration numbers for network training are tried and the selection of the best model was based on the mean absolute percentage error MAPE of 1%. The effect of temperature to the the peak hourly load forecast captured by NARXNET with temperature model that outperformed ARIMA transfer function with temperature model that results with small forecast error measured in MAPE of less than 1% could not be ignored as temperature is one the intervening factors in Malaysia regional load forecasting.

The last part of chapter 3 presents the daily load profiles on 1st January at the stations for the period of three years from 2006 to 2008 in the form of graphs. The trends and patterns of peak load consumption are analyzed and discussed in the last chapter.

Chapter 4 discusses, compares and assess the results of data analysis from all the models involved in the research.

Chapter 5 summarizes and concludes the outcome of the research and proposes recommendations for future related research topics.

1.5 Thesis Contribution

The results of the implemented regional peak hourly load forecasting using Narx Neural Network with temperature model will contribute to the improvement in the peak hourly load forecast for an hourly ahead, a week ahead and the five hundreds -hours interval ahead. The ability of the model to capture the effect of temperature on the peak hourly load system and to predict the peak hourly load with small errors of forecast and speedy computing time is expected to improve on the load forecast and thus will be beneficial to the future planning and operations of the power system.

The implementation of improved load forecasting model using neural network approach that has the ability to recognize the data pattern occurring on any time of the chosen interval would hopefully result with more accurate and reliable forecasts of peak load demand. Hence the implemented model can be applied to other real world time series problems in economics, social sciences and others.

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