

**LOAD FORECASTING BASED ON NEURAL NETWORK
APPROACH**

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**BACHELOR OF ELECTRICAL ENGINEERING WITH
HONORS**

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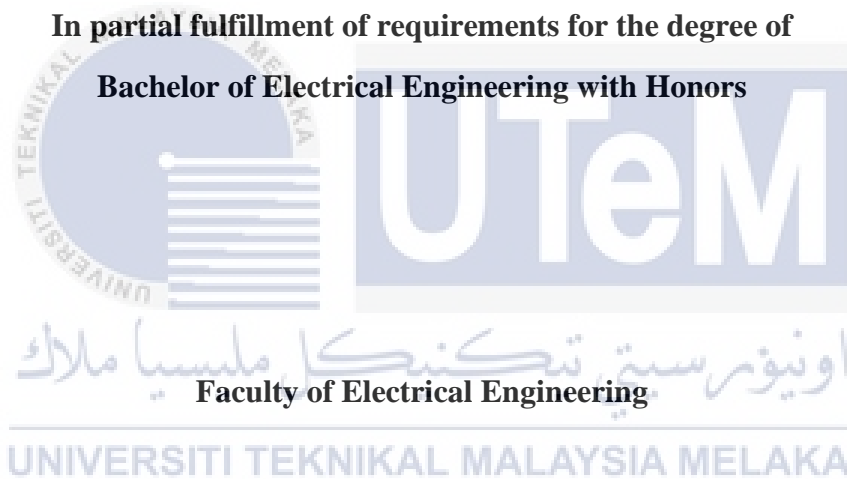
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LOAD FORECASTING BASED ON NEURAL NETWORK APPROACH

NUR YUSRINA BINTI AZIZAN

A report submitted

**In partial fulfillment of requirements for the degree of
Bachelor of Electrical Engineering with Honors**



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2021

DECLARATION

I declare that this thesis entitled “LOAD FORECASTING BASED ON NEURAL NETWORK APPROACH” is the result of my own research except as cited in the references. The thesis has not been accepted by any degree and is not currently submitted in candidature of any other degree.

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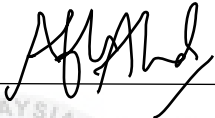
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5th JULY 2021



APPROVAL

I hereby declare that I have checked this report entitled “LOAD FORECASTING BASED ON NEURAL NETWORK” and in my opinion, this thesis it complies the partial fulfillment for awarding the award of the degree of Bachelor of Electrical Engineering with Honors.

Signature :  _____

Name : DR. ARFAH BINTI AHMAD _____

Date : 5th JULY 2021 _____



DEDICATIONS

To my beloved mother and father



ACKNOWLEDGEMENTS

In the name of Allah, the most Gracious and the most Merciful

All graceful praises to Allah for the strengths and His blessing in completing this project.

Without the participation and help of so many people whose names may not all be enumerated, the completion of this undertaking could not have been possible. Their contributions are sincerely appreciated and recognized with gratitude. However, I particularly wish to express my biggest appreciation to my main project supervisor, Dr. Arfah Binti Ahmad for her guidance, patience, enthusiasm and constant support. She contributes a lot to the success of this project by offering constructive comments and suggestions throughout this project. I am truly grateful for all the time she has spent on proofreading and correcting my mistakes throughout the project process.

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ABSTRACT

This project focuses on the load forecasting using neural network approach. Load forecasting is a process of estimating the amount of power load usage in future. It is a crucial step for the electrical utility company to produce an optimum amount of power load supply. The electrical load should not be produced less than its demand as it can cause blackout due to power shortage. However, the power load supply should also not be produced more than its demand because it will be a waste as power load cannot be stored and this will cost the electrical utility company. Therefore, load forecasting should be done before the power load supply is produce. The objective of this project is to pre-process the load data taken from Peninsular Malaysia and to forecast the load based on previous load data. Neural network is the approach used in this project to forecast the load data. Long Short-Term Memory (LSTM) is a particular type of recurrent neural network that are designed to avoid the long-term dependency problem. Its strength is in remembering the information for long period of time. Therefore, it is suitable for the load data used in this project as the load data reading is for three months. The three months load data are being grouped by the same day in order to observe the load consumption pattern. Then, LSTM structure is modeled to forecast the load data more accurately and considered acceptable when the Root Mean Squared Error (RMSE) is equal or lower than 100. In this project, the energy load data for a week is successfully forecasted via Neural Network approach which is Long Short Term Memory (LSTM) technique and the best LSTM structure that give the least error and predict accurately is successfully identified.

ABSTRAK

Projek ini memfokuskan kepada ramalan penggunaan tenaga menggunakan pendekatan rangkaian neural. Ramalan penggunaan tenaga adalah proses menganggarkan jumlah penggunaan tenaga kuasa elektrik pada masa akan datang. Ia adalah Langkah yang penting bagi syarikat utiliti elektrik untuk menghasilkan jumlah bekalan beban kuasa yang optimum. Tenaga elektrik tidak boleh dihasilkan kurang daripada permintaannya kerana ia boleh menyebabkan terputusnya bekalan elektrik kerana kekurangan kuasa. Walau bagaimanapun, bekalan tenaga juga tidak boleh dihasilkan lebih daripada permintaannya kerana ia akan menjadi satu pembaziran kerana beban kuasa tidak boleh disimpan dan ini akan merugikan syarikat utiliti elektrik. Oleh itu, ramalan penggunaan tenaga perlu dilakukan sebelum bekalan beban kuasa dihasilkan. Objektif projek ini adalah untuk memproses data penggunaan tenaga yang diambil dari Semenanjung Malaysia dan meramalkan penggunaan tenaga berdasarkan data penggunaan tenaga sebelumnya. Rangkaian neural adalah pendekatan yang digunakan dalam projek ini untuk meramal data penggunaan tenaga. Long Short-Term Memory (LSTM) adalah sejenis rangkaian neural berulang yang direka untuk mengelakkan masalah pergantungan jangka panjang. Kekuatannya adalah dalam mengingati maklumat untuk jangka masa yang panjang. Oleh itu, ia sesuai untuk data penggunaan tenaga yang digunakan dalam projek ini kerana bacaan data penggunaan tenaga yang digunakan adalah selama tiga bulan. Data beban tiga bulan dikelompokkan pada hari yang sama untuk memerhatikan corak penggunaan beban. Kemudian, struktur LSTM dimodelkan untuk meramalkan data muatan dengan lebih tepat dan dianggap dapat diterima apabila Root Mean Squared Error (RMSE) sama atau kurang dari 100. Dalam projek ini, data beban tenaga selama seminggu berjaya diramalkan melalui Neural Network pendekatan yang merupakan teknik Long Short Term Memory (LSTM) dan struktur LSTM terbaik yang memberikan ralat paling sedikit dan meramalkan dengan tepat berjaya dikenal pasti.

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CHAPTER 1

INTRODUCTION

This chapter focuses on electrical load, electrical load classification, purpose of load forecasting and load forecasting in Malaysia.

1.1 Project Background

An electrical load is the part of an electrical circuit in which current, like a resistor and a motor, is converted into something useful. A load converts heat, light, or motion into electricity. In other words, the portion of a circuit connecting to a well-defined output is also regarded as an electrical load. At any given time, electric load may also be said to be the sum of energy on the grid, as it makes its journey from the power source to all the households, companies, and factories within the territory of a utility. Different factors can be classified by electrical load. Electrical load classifications include resistive load, capacitive load, and inductive load [1]. In the power grid, there are also different kinds of loads, such as domestic load/residential load, commercial load, industrial load, municipal load, irrigation load and traction load. Electricity is something that cannot be stored and used later. Once it is produced, it must be used and live on the grid or else it will be lost. Managing and changing how much load is on the grid at any given time is one way that utilities manage product prices for their customers. To ensure that it is the correct amount to satisfy the clients' real-time needs, they must track both demand and load around the clock. Thus, load forecasting is needed. Load forecasting allows an energy provider to make major decisions, including decisions on the purchase and generation of electricity, load switching, and the construction of infrastructure. The demand for electricity in Malaysia forms the basis for the planning of the power grid, power conservation and supply reliability. The need for load forecasting that assesses electricity demand is underlined by the 2005 blackouts for the whole of Malaysia [2]. In recent years, the importance of forecasting demand for the utility sector has become a much-discussed topic that has led to the creation in the last two decades of new tools and methods for forecasting.

1.2 Motivation

Load demand is data from a time series and is one of the key input factors for economic growth, especially in developing countries such as Malaysia. It is hoped that high-precision load demand forecasting would enable Malaysian electricity utility company to generate the necessary adequate load and avoid energy waste and prevent system failure. Load forecasting enables a single national electricity grid to operate optimally. This is appropriate during the time under investigation to meet power demands and satisfy customer electrical energy needs, and to prepare only for the items that are requested. The forecast of electricity demand is seen as one of the crucial factors for the economic activity of power systems. Precise load forecasting holds a great saving opportunity for electric utility companies, according to Bunn and Farmer [3]. When load forecasting is used to manage operations and decisions, the maximum savings can be obtained.

An adequate model for electric power load forecasting involves the operation and planning of a power utility corporation. Load forecasting succor and electric utility to draw conclusions about the decision to produce and buy electric power, load switching, voltage control, reconfiguration of the network and construction of infrastructure [5]. With fluctuating supply and demand and shifts in weather and energy prices increasing by a factor of ten or more during peak situations, load forecasting is critical. Short-term load forecasting can assist in predicting load flows and making choices that can stop overloading. Timely adoption of such decisions leads to improving the reliability of the network and decreasing the occurrence of system failures and blackouts.

1.3 Problem Statement

The National Electricity Utility Company of Malaysia, Tenaga Nasional (TNB) serves over six million customers across Malaysia. Electricity generation, transmission, and distribution are its core activities. The Transmission Division is responsible for the entire range of transmission operations, including system planning, evaluation, implementation, and maintenance of transmission properties. The load forecast is one of the criteria of system planning [15]. The most important tasks in electricity engineering are electric power load and power demand forecasting. The precise analysis of such points

will allow the conditions for sustainable supplementation of energy to be determined. Electrical energy, however, cannot be retained. Whenever there is a market for it, it must be created. Therefore, it is imperative that the load on their grid be calculated in advance for the electricity utilities. This load prediction is known as forecasting of loads.

1.4 Objectives

1. To pre-process the electrical load data for three months taken in Peninsular Malaysia
2. To forecast the load data via Neural Network approach which is the Long-Short Term Memory (LSTM) technique
3. To identify the best LSTM structure that give the least error and predict accurately

1.5 Scope

The scope of this project is to forecast the load usage in future using Neural Network approach which is Long-Short Term Memory (LSTM). The period of electrical load data used for training the LSTM is only 12 weeks and it is taken from Peninsular Malaysia. LSTM is the only forecasting method used in this project and the best LSTM structure that forecast the data accurately will be modeled. The accuracy of LSTM is defined via error calculations, that are Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE).

CHAPTER 2

LITERATURE REVIEW

In this chapter, theories about load forecasting, Long Short Term Memory and neural network will be discussed. In addition, previous studies about load forecasting and the available method used to forecast the electrical load is also being explained in detail to get better understanding about how the method works.

2.1 Load Forecast

Load forecasting is a method for estimating the demands of potential loads. In order to ensure that adequate generation is available to cope with growing demand, it is necessary for power system planners and demand controllers [11]. A detailed load forecast model can result in better financial management, scheduling of maintenance and management of fuel. In terms of a few significant technological and economic implications, load forecasting plays an important role in power system operations. The analysis and management of many activities such as energy storage management, future energy contracts, power plants maintenance schedule and portfolio structuring need the forecasting of load and power demand [7].

2.1.1 Categories of Load Forecasting Method

The load forecasting can be divided into three categories namely as Short-term load forecasting, Medium term load forecasting and Long-term load forecasting [10]. Table 2.1 shows the categories of load forecasting method.

Table 2.1 Categories of Load Forecasting Method

Categories of load forecasting method	Feature
Short term load forecasting [10]	<ul style="list-style-type: none">• The time ranges from 1 hour to 1 week• Prompt the user to make decisions that can predict load flow and prevent overloading

	<ul style="list-style-type: none"> • Short term forecasting is used to provide required information for regular operations system management and unit commitment.
Medium term load forecasting [10]	<ul style="list-style-type: none"> • The time ranges from 1 week to 1 year. • For various operations within a utility corporation, the forecast for different time horizons is important. • For the purposes of coordinating fuel supplies and unit management, medium term forecasting is often used.
Long term load forecasting [10]	<ul style="list-style-type: none"> • The time range is for more than 1 year. • Used to provide the management of electric utility companies with reliable estimation of potential needs for growth, procurement of equipment or recruiting of employees.

2.1.2 Traditional Forecasting Techniques

These predictions or forecasts were made using traditional mathematical methods in the early days. These techniques have been improved by the development of advanced methods with the discovery of research for more efficient forecasting in different fields of study [10]. Table 2.2 shows the traditional techniques of load forecasting.

Table 2.2 Traditional Techniques of Load Forecasting [10]

Traditional Forecasting Technique	Features
Regression Method	<ul style="list-style-type: none"> • The most frequently used statistical approaches and are also simple to implement. • Typically used to model the load consumption relationship with other variables, such as weather conditions, types of days and customer groups. • This technique assumes that the load can be split into a normal load trend and a trend that is linearly dependent on certain load-influencing factors.

	<ul style="list-style-type: none"> • The precision of the method relies on historical data to accurately reflect potential future conditions, but it is simple to construct a measure to classify any inaccurate prediction. • This technique consists of a transformation function with translation and reflection techniques.
Multiple Regression	<ul style="list-style-type: none"> • The most common technique used to predict the load affected by several variables. • Multiple regression analysis for load forecasting uses the least-square estimation method.
Exponential Smoothing	<ul style="list-style-type: none"> • The first load is a model based on previous data, and then the future load is projected using this model. • The Winter's method is one of existing exponential smoothing techniques capable of explicitly evaluating seasonal time series directly. For stationary, trend, and seasonality, it is based on three smoothing constants. • Exponential smoothing in the hybrid system was improved by power spectrum analysis and adaptive autoregressive modeling.
Iterative Reweighed Least-Squares	<ul style="list-style-type: none"> • Used for the model order and parameters to be defined. This technique uses an operator that controls one variable at a time and specifies the optimum point of departure. • To define a suboptimal model of load dynamics, the autocorrelation function and the partial autocorrelation function of the resulting separated past load data are used. • In identifying an ideal model and the corresponding parameter estimates, a three-way decision variable is generated by the weighting function, the tuning constants and the weighted sum of the square residuals.

2.1.3 Modified Traditional Techniques

Traditional forecasting techniques have been updated so that, under changing environmental conditions, they can automatically correct the parameters of the forecasting model. Adaptive load forecasting, stochastic time series and support vector machine-based techniques are some of the techniques that are the adapted version of conventional techniques. Table 2.3 shows the features of modified traditional techniques of load forecasting.

Table 2.3 Modified Traditional Techniques of Load Forecasting [10]

Modified Traditional Technique	Features
Adaptive Demand Forecasting	<ul style="list-style-type: none"> • To keep track of the changing load conditions, demand forecasting model parameters are automatically corrected. • Demand forecasting is adaptive in nature and can also be used in the Utility Control System as an online software kit. • The state vector is calculated using existing forecast errors and current programs for the acquisition of weather data. The state vector is defined by the historical data set analysis. • This approach has two unique features: <ul style="list-style-type: none"> ➤ or the control of cyclic patterns, autocorrelation optimization is used. ➤ in addition to updating model parameters, the time series structure and order can be adapted to new conditions

<p>Stochastic Time Series</p> <ul style="list-style-type: none"> ➤ Autoregressive (AR) Model ➤ Autoregressive Moving-Average (ARMA) Model ➤ Autoregressive Integrated Moving-Average (ARIMA) Model 	<ul style="list-style-type: none"> • The techniques of the Time series tend to be among the most common approaches to STLF. • Time series strategies are based on the premise that the information has an internal structure, such as time series, pattern or seasonal changes.
<p>Support Vector Machine based Technique</p>	<ul style="list-style-type: none"> • A modern, powerful method of machine learning based on the theory of statistical learning (SLT) • Analyzes information and accepts trends used for classification and regression analysis

2.1.4 Soft Computing Techniques

The Soft Computing approach has emerged to deal efficiently and most effectively with such models in the research scenario. For the last few decades, it has been very commonly used. Soft computing is an evolving approach which, in an unstable environment and imprecision, parallels the remarkable development of the system mind to reason and learn. It is increasingly evolving as a method to help intelligent computer-based systems emulate the human mind's ability to use approximate rather than precise modes of reasoning[13]. The basic theme of soft computing is that accuracy and certainty carry a cost and that the tolerance for imprecision and ambiguity should be exploited by intelligent systems whenever possible. Soft computing constitutes a collection of disciplines which include fuzzy logic (FL), neural networks (NNs), evolutionary algorithms (EAs) like genetic algorithms (GAs) and Knowledge Based system. Table 2.4 shows the features of soft computing techniques[14].

Table 2.4 Soft Computing Techniques [10]

Soft Computing Techniques	Function
Genetic Algorithms / Evolutionary Programming	<ul style="list-style-type: none"> • Used to describe the autoregressive moving average for load demand forecasts using an exogenous variable (ARMAX) model • Algorithm can converge by simulating natural evolutionary process to the global extreme of a complex error surface • Simulates the mechanism of natural evolution and constitutes an algorithm for stochastic optimization • Capable of converging asymptotically towards the desired global solution and can thus increase the model's fitting accuracy.
Fuzzy Logic	<ul style="list-style-type: none"> • The centroid defuzzification fuzzy logic system will define and estimate any unknown dynamic system or load on the compact set to arbitrary accuracy. • Has great ability to draw parallels from enormous data • Fuzzy logic-based forecasters operate in two phases: training and on-line forecasting <ul style="list-style-type: none"> ➤ Training stage: calculated historical load information is used to train a 2m-input, 2n-output fuzzy-logic-based forecaster to generate a database of patterns and a fuzzy rule base by using first and second-order data differences
Neural Networks	<ul style="list-style-type: none"> • It is capable to learn based on given input • Provide the ability to resolve dependence on a functional version of a model for forecasting • There are many kinds of neural networks including multilayer perceptron network and self-organizing network

	<ul style="list-style-type: none"> • Most of the forecasting methods does not require a load model
Knowledge-Based Expert Systems	<ul style="list-style-type: none"> • A computer program capable of thinking, describing, and expanding its knowledge base as new data becomes accessible to it. • The 'information engineer' derives load forecasting knowledge from an expert in the field through what is called the expert system's knowledge base portion to construct the model. • This understanding is expressed as facts and IF-THEN rules and consists of a series of relationships. • In order to establish different rules for different methods, the logical and syntactic relationships between weather load and the predominant regular load types were widely studied.

2.2 Long Short-Term Memory (LSTM)

A special type of recurrent neural networks is the long short-term memory (LSTM) networks. It is capable of learning long-term dependencies. On different kinds of concerns, LSTM works very well and is commonly used. LSTM is explicitly designed to prevent the long-term dependence issue. It was possible to circumvent the issue of the declining error gradients in the LSTM networks. An LSTM network is usually controlled by recurrent gates called “forgetting” gates. Errors are propagated back in time through a potentially unlimited number of virtual layers. In this way, learning takes place in LSTM, while preserving the memory of thousands and even millions of time intervals in the past. In accordance with the specifics of the project, network topologies such as LSTM can be created. In addition, wide delays between major events can be considered in an LSTM network, and high-frequency and low-frequency components can thus be combined [8].

The recurring neural networks are all in the form of a chain of repeated neural network modules. LSTM also has a chain structure like that, but there is a different structure to the repeating module. Four neural layers exist, and they communicate in a special way. Figure 2.1 shows that each line transmits an

entire vector from one node's output to the others' inputs. While yellow rectangles are trained layers of the neural network, pink circles represent pointwise operators. Merging lines imply concatenation, while branching lines indicate duplicating their contents and sending duplicates to separate locations.

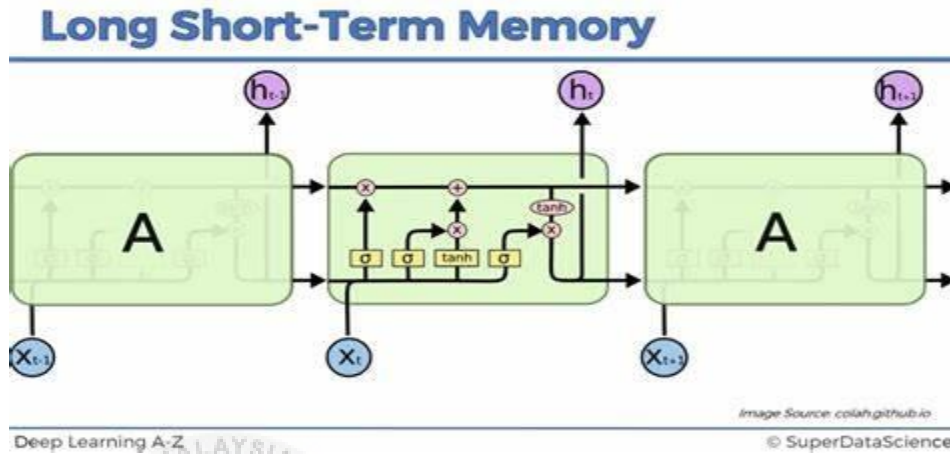


Figure 2.1 LSTM Cell Structure [8]

2.2.1 Architecture of LSTM

Multiple LSTM unit architectures exist. A typical architecture is composed of a cell that is the LSTM unit's memory portion and three regulators, typically information flow gates within the LSTM unit that are an input gate, an output gate, and a forgotten gate. Some of the LSTM unit variants may not have one or both gates, or maybe other gates [8]. Figure 2.2 shows the structure of one LSTM cell.

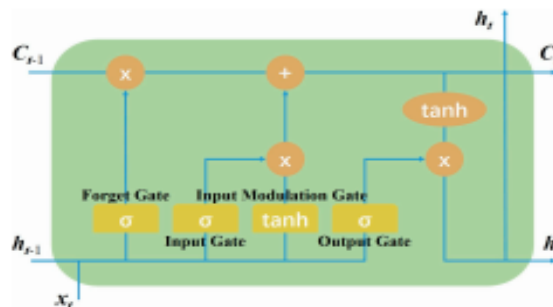


Figure 2.2 shows the structure of an LSTM cell [8]