ELECTRICITY LOAD FORECASTING FOR POWER SYSTEM PLANNING AND OPERATION BY USING ARTIFICIAL NEURAL NETWORK

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DEDICATION

This project report is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

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ABSTRACT

The electrical power system performance is obtained when generation keeps pace with demand. The generation, transmission, and distribution companies need a method for forecasting electrical load to maximize the security, efficiency, and economic utilization of their electrical infrastructure. The necessity of an appropriate model for forecasting the short-term electric power load provides the information required for the system's routine process management and unit commitment. The STLF has many notable merits, including reduction of operational costs, maintains the efficiency of energy markets, and provide a deeper understanding of the monitored system's dynamics. The STLF indicates the anticipated electric load for a time period ranging from a few hours to a few days. This is accomplished by inputting the day's form, hour, temperature, previous day loads, previous week loads and previous 24-hour loads into the proposed algorithm to forecast the short-term load. An Artificial Neural Network is created using the MATLAB2021a Simulation Software to validate the proposed Back Propagation algorithm's efficiency. The Artificial Neural Network is a mathematical method that simulates the human brain's thought processes. The Artificial Neural Network can be built and trained to take previous load data and the weather information as inputs and gives an output of the forecasted load. Thus, there are some missing data in the dataset that will surely affect the system's accuracy. Therefore, the forecasting accuracy was evaluated by calculating different error metrics such as the MAPE, the MAE, the APE, the Daily Peak error, the MSE and the derived RMSE. For the proposed algorithm, the range of some hourly load forecasting error metrics lies between 1934378.64MW^2 and 579905.75MW^2 for the MSE, 2.97% and 6.17% for the Daily Peak error, and 3.15% and 6.54% for the MAPE. On the other hand, the overall MAPE of the proposed system is 5.9% error, while the compared multiple linear regression model gives an overall MAPE of 10.43% error. Therefore, the proposed model has least error than the MLRM. The proposed back propagation algorithm results demonstrate the method's superior performance and demonstrate that it can be used in realistic systems for forecasting short-term electricity load.

ABSTRAK

Prestasi sistem kuasa elektrik diperoleh apabila penjanaan seiring dengan permintaan. Syarikat penjanaan, penghantaran dan pengedaran memerlukan kaedah untuk meramalkan beban elektrik untuk memaksimumkan keselamatan, kecekapan dan penggunaan ekonomi infrastruktur elektrik mereka. Keperluan model yang sesuai untuk meramalkan beban kuasa elektrik jangka pendek menyediakan maklumat yang diperlukan untuk pengurusan proses rutin sistem dan komitmen unit. STLF mempunyai banyak merit yang ketara, termasuk pengurangan kos operasi, mengekalkan kecekapan pasaran tenaga, dan memberikan pemahaman yang lebih mendalam tentang dinamik sistem yang dipantau. STLF menunjukkan beban elektrik yang dijangkakan untuk tempoh masa antara beberapa jam hingga beberapa hari. Ini dicapai dengan memasukkan borang hari, jam, suhu, beban hari sebelumnya, beban minggu sebelumnya dan beban 24 jam sebelumnya ke dalam algoritma yang dicadangkan untuk meramalkan beban jangka pendek. Rangkaian Neural Tiruan dicipta menggunakan Perisian Simulasi MATLAB2021a untuk mengesahkan kecekapan algoritma Back Propagation yang dicadangkan. Rangkaian Neural Buatan ialah kaedah matematik yang menyerupai proses pemikiran otak manusia. Rangkaian Neural Buatan boleh dibina dan dilatih untuk mengambil data beban sebelumnya dan maklumat cuaca sebagai input dan memberikan output beban yang diramalkan. Ketepatan ramalan telah dinilai dengan mengira metrik ralat yang berbeza seperti MAPE, MAE, APE, ralat Puncak Harian, MSE dan RMSE terbitan. Untuk algoritma yang dicadangkan, julat beberapa metrik ralat ramalan beban setiap jam terletak antara 1934378.64MW2 dan 579905.75MW2 untuk MSE, 2.97% dan 6.17% untuk ralat Puncak Harian dan 3.15% dan 6.54% untuk MAPE. Sebaliknya, MAPE keseluruhan sistem yang dicadangkan ialah 5.9% ralat, manakala model regresi linear berganda yang dibandingkan memberikan MAPE keseluruhan ralat 10.43%. Oleh itu, model yang dicadangkan mempunyai ralat paling sedikit daripada MLRM. Keputusan algoritma perambatan belakang yang dicadangkan menunjukkan prestasi unggul kaedah dan menunjukkan bahawa ia boleh digunakan dalam sistem realistik untuk meramalkan beban elektrik jangka pendek.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
AR	-	Auto-Regressive
ARIMA	-	Auto-Regressive Integrated Moving Average
ARIMAX	-	Auto Regressive Integrated Moving Average with Exogeneous Input
ARMA	-	Auto-Regressive Moving Average
BNN	-	Bayesian Neural Network
BP	-	Back-Propagation
BPNN	-	Back-Propagation Neural Network
DPE		Daily Peak Error
EMS	-	Energy Management System
ES	-	Expert System
GP	-	Gaussian Process
GUI	-	Graphical User Interface
IBNN	-	Improved Bayesian Neural Network
ISO	-	International Organization for Standardization
LOLIMOT	-	Locally Linear Model Tree
LSTM	-	Long Short-Term Memory
LTLF	-	Long Term Load Forecasting
MAE	-	Mean Absolute Error
MAPE	-	Mean Absolute Percentage Error
MATLAB	-	Matrix Laboratory
MLP	-	Multi-Layer Perceptron
MLPNN	-	Multi-Layer Perceptron Neural Network
MSE	-	Mean Square Error
MTLF	-	Medium Term Load Forecasting
NF	-	Neuro-Fuzzy
NN	-	Neural Network
RMSE	-	Root Mean Square Error

SARIMA	-	Seasonal Auto-Regressive Integrated Moving Average
STLF	-	Short Term Load Forecasting
SVM	-	Support Vector Machine
SVR	-	Support Vector Regression

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CHAPTER 1

INTRODUCTION

1.1. Background of the Study

According to some studies reviewed, one of the most significant factors in economic growth is the availability of electrical power [1]. So, it goes without saying that the world's main resources are now energy. This energy is used in our everyday lives, such as electricity, refined oils, liquefied petroleum gas, and photovoltaic, and wind, as well as well as being found in various kinds of batteries. To ensure consumers have an uninterrupted supply of electricity, it is essential to conduct an accurate assessment of current and future power demand [2]. The method of predicting forthcoming electric load using previous load and weather data as well as current and forecasted weather data is known as electric load forecasting. Numerous models have been established over the last few decades to improve forecasting of electric load [3].

A power utility's operation and planning require an appropriate model for forecasting electric power load [3], in order to forecast the amount of power required to meet demand. It outlines the present and future scenario for load demand. It has a range of applications including load switching, energy procurement and generation, infrastructure development and contract evaluation [2]. Load projections play a key role in helping an electricity company to decide on important issues in energy production, transmission, distribution [3]. To participate in the market, a participant must have a reliable estimate of the amount of energy required at a given time. As a result, almost all energy market decisions are based on load forecasting. For a utility company's operation and planning, accurate predictive electricity load models are crucial [4].

To continue to help economic development and meet future energy demands, load forecasting has become a critical challenge for electric utilities [5]. Additionally, a precise load forecast will aid in the development of a power supply policy, financial planning, market analysis, and energy management [1]. It helps electrical power establishments to make crucial choices, decreases production expenses, and enhances productivity and accuracy. The calculation of the electric load uses two key parameters: electricity (MW, kW) and electricity (MWh, kWh). Many investigations have tried to establish a sound and precise system for forecasting power loads. These studies examined a variety of input characteristics related to customer behaviour and characteristics that have a direct effect on the electrical load [6].

Calendar data, weather information like (temperature, wind speed, air pressure, humidity), day types (working or vacation) and previous load are all assumed as input variables. The goal is to create a connection between the system's inputs (or input variables) and its outputs (or power load). The power load varies at random during the day and has different values from one day to the next and from season to next season [6]. Forecasting load is critical for energy providers, financial institutions, and other players in the generation, transmission, distribution, and market of electric energy [5]. Forecasting loads can be divided into three broad classes: LTLF (Long term load forecast) used to forecast potential growth, equipment acquisitions, and personnel recruiting requirements for electric utility companies. Medium-term forecasting used to schedule fuel deliveries and preventative maintenance on the unit. Short term predictions used to provide necessary data for regular operational management and unit commitment management [3].

If the anticipated loads are forecast with insufficient precision, any planned plan would be out of step with reality and therefore unusable. As a result, one of the study's goals is to expand the accuracy of demand predicting. As a primary engineering analysis, load forecasting can be divided into distinct forecasts based on forecasting periods, such as real-time and long-term forecasting. Wherever electric load forecasting is most widely applied, it's known as STLF [7]. STLF (Short term load forecast) could be specified and implemented separately for electrical customers and high voltage substations. This study proposes and explicitly demonstrates an algorithm for STLF. STLF estimates the load, regular peaking load, and daily and weekly output of energy for every hour of the day. Artificial Neural Networks (ANN) are a subset of artificial intelligence techniques that are capable of creating and using profile patterns in the most popular short-term load forecast approach. The projected load profile's accuracy is entirely dependent on the input and output variables chosen ANN models [7].

1.2. Problem Statement

One of the most important inputs in economic growth is electricity, the energy is the most widely used commodity in today's world and it can be used in a variety of ways in our daily lives. It is defined as the total amount of power required by consumers. Additionally, the term "demand capacity" or "energy consumption" is used. The electrical output varies, and cannot always be stored effectively. As a consequence, it is critical to sustain the amount of energy generated in order to meet demand at a given time. In order to provide customers with an uninterrupted supply of energy, there is a need to estimate consumers' energy requirements and the amount of electricity that power providers should generate in order to meet energy demand and support economic growth in the future. Load forecasting enables accurate estimation of current and potential electricity demand. STLF is a technique that forecasts demand with a lead time of one hour to seven days for proper scheduling and operation of power system utilities. It has been a critical component of EMS (Energy management system) since their inception. As a result, STLF is critical for effective and profitable management of electrical utilities.

1.3. Objectives of the Report

- ✓ To investigate the most appropriate neural network architecture for forecasting Electricity load.
- ✓ To develop a technique for predicting short-term electricity load for utilities using an artificial neural network.
- ✓ To evaluate the technique's performance in terms of accuracy and efficiency by making different error metrics including MAPE, MAE, MSE RMSE, daily peak error and the regression analysis.

1.4. Research Question

- ✓ What kind of neural network architecture would have the best performance in predicting electrical demand?
- ✓ How to devise a strategy for utilities using artificial neural networks to predict short-term electricity load?
- ✓ How to determine the accuracy and efficiency of ANN technology by performing different error metrics including MAPE, MAE, MSE RMSE, daily peak error and the regression analysis.

1.5. Significance of the Report

Forecasting load is critical for the deregulated electric industry. Numerous mathematical techniques had been established for forecasting demand. Accurate predicting techniques for short-term electric power demand are critical for a utility company's service and planning. Load forecasting enables electricity companies to take critical decisions about power procurement and generation, load switching, and infrastructure construction. Forecasting load is critical for energy providers, ISOs, national agencies, and other contributors in the production, transmission, distribution, and market of electric energy [2].

The main significance of the study includes:

- ✓ Minimize the risks for the utility company. Understanding the future long-term load helps the company to plan and make economically viable decisions in regard to future generation and transmission investments.
- ✓ Helps to determine the required resources such as fuels required to operate the generating plants as well as other resources that are needed to ensure uninterrupted and yet economical generation and distribution of the power to the consumers. This is important for short-, medium-, and long-term planning.
- ✓ The load forecasting helps in planning the future in terms of the size, location and type of the future generating plant. By determining areas or regions with high or growing demand, the utilities will most likely generate the power near the load. This minimizes the transmission and distribution infrastructures as well as the associated losses.

- ✓ Helps in deciding and planning for maintenance of the power systems. By understanding the demand, the utility can know when to carry out the maintenance and ensure that it has the minimum impact on the consumers. For example, they may decide to do maintenance on residential areas during the day when most people are at work and demand is very low.

1.6. Scope of the Report

This research focuses on predicting market demand and the precise capacity to produce for a short-term timeframe in order to estimate the amount of power required to meet demand, this study will not forecast the price and it is only limited for short term load forecast.

The scope and limitation of the study are as follow:

- ✓ This study is focused on short term electricity load forecasting, the significant data that is required in this study is limited to the historical load data and the weather information.
- ✓ The proposed ANN architecture is developed on the MATLAB Platform to forecast the short-term load using the secondary data.

1.7. Organization of the Report

This dissertation is organized into five chapters. The first chapter addresses the meaning of the analysis, problem statement, objectives, research questions, and scope of the study. The second chapter will go further into the project's philosophy and literature review. It is explained the numerous related works to this project that used various methods to forecast the load, a summary of load forecasting, the factors affecting load forecasting, the different forms of load forecasting, load forecasting techniques, and the load forecasting errors. Chapter three develops an ANN technique on the MATLAB Platform for forecasting short-term load using the secondary data collected while chapter four discusses the findings of the study. Finally, chapter five will address the project's conclusions and suggestions for future work.

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