

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.

## **ACKNOWLEDGEMENT**

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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  $1934378.64\text{MW}^2$  and  $579905.75\text{MW}^2$  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 1934378.64MW<sup>2</sup> dan 579905.75MW<sup>2</sup> 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.

## TABLE OF CONTENTS

	<b>TITLE</b>	<b>PAGE</b>
	<b>DECLARATION</b>	<b>iii</b>
	<b>DEDICATION</b>	<b>iv</b>
	<b>ACKNOWLEDGEMENT</b>	<b>v</b>
	<b>ABSTRACT</b>	<b>vi</b>
	<b>ABSTRAK</b>	<b>vii</b>
	<b>TABLE OF CONTENTS</b>	<b>viii</b>
	<b>LIST OF TABLES</b>	<b>xiv</b>
	<b>LIST OF FIGURES</b>	<b>xv</b>
	<b>LIST OF ABBREVIATIONS</b>	<b>xx</b>
	<b>LIST OF APPENDICES</b>	<b>xxii</b>
<b>CHAPTER 1</b>	<b>INTRODUCTION</b>	<b>1</b>
	1.1. Background of the Study	1
	1.2. Problem Statement	3
	1.3. Objectives of the Report	3
	1.4. Research Question	4
	1.5. Significance of the Report	4
	1.6. Scope of the Report	5
	1.7. Organization of the Report	5
<b>CHAPTER 2</b>	<b>LITERATURE REVIEW</b>	<b>6</b>
	2.1 Introduction	6
	2.2 Overview of Load Forecasting	6
	2.3 Related Work	7
	2.4 Power Load Forecasting	11
	2.5 Factors Affecting Load Forecasting	13
	2.5.1 Time Factor	13
	2.5.2 Economic Factor	13

2.5.3	Weather Factor	14
2.5.4	Humidity	15
2.5.5	Occasional Spikes	15
2.6	Load Forecasting Techniques	15
2.6.1	Time Series Analysis	16
2.6.2	Regression based Approach	17
2.6.3	Support Vector Machines	17
2.6.4	Artificial Neural Networks	18
2.6.4.1	Types of Functions of Neurons	20
2.6.5	Expert systems	21
2.6.6	Fuzzy Logic	21
2.7	Benefits of Load Forecasting	21
2.8	Challenges of Load Forecasting	22
2.9	Load Forecast Errors	23
2.10	Problem Formulation	25
<b>CHAPTER 3</b>	<b>METHODOLOGY</b>	<b>26</b>
3.1	Introduction	26
3.2	System Specifications	26
3.2.1	Block Diagram for Short Term Load Forecasting	27
3.2.2	Flow Chart of the System	29
3.3	Input Parameters	29
3.3.1	Introduction	29
3.3.2	Analysis of Input Parameters	30
3.3.2.1	Load Consumption Profile Curve	30
3.3.2.2	Summary of Load Consumption Curve	32
3.3.2.3	Load vs Temperature Correlations	32
3.3.2.4	Summary of Load Vs Temperature Correlation	34
3.4	Multi-layer Perceptron NN	34
3.4.1	Introduction	34

3.4.2	Back Propagation Error	35
3.4.3	Performance Evaluation of Neural Network	35
3.5	MATLAB Platform	36
3.6	Research Design Specification	37
3.7	Research Design Matrix	38
3.8	Research Design Time-Line	38
<b>CHAPTER 4</b>	<b>PROPOSED ALGORITHM</b>	<b>39</b>
4.1	Back Propagation Algorithm	39
4.2	Back Propagation Neural Network	41
4.2.1	Learning Process of Back propagation Algorithm	42
4.2.2	Back Propagation Neural Network Input Layer	42
4.2.3	Back Propagation Neural Network Hidden Layer	42
4.2.4	Back Propagation Neural Network Output Layer	43
4.3	ANN Implementation	43
4.3.1	Levenberg-Marquardt Training Algorithm	43
4.4	Flow Chart of Back Propagation Algorithm	45
<b>CHAPTER 5</b>	<b>RESULTS &amp; DISCUSSION</b>	<b>46</b>
5.1	Overview	46
5.2	Load Forecasting Analysis	46
5.3	Load Forecasting Analysis by Years	56
5.3.1	Load Forecasting Analysis for 2004	56
5.3.2	Load Forecasting Analysis for 2005	57
5.3.3	Load Forecasting Analysis for 2006	58
5.3.4	Load Forecasting Analysis for 2007	59
5.3.5	Load Forecasting Analysis for Jan-June 2008	60
5.4	Load Forecasting Analysis by Selected Months	61
5.4.1	Feb-2004 Load Forecasting Analysis	61
5.4.2	March-2004 Load Forecasting Analysis	61
5.4.3	April-2004 Load Forecasting Analysis	62



5.4.4	April-2005 Load Forecasting Analysis	63
5.4.5	May-2005 Load Forecasting Analysis	63
5.4.6	Aug-2005 Load Forecasting Analysis	64
5.4.7	July-2006 Load Forecasting Analysis	65
5.4.8	Sep-2006 Load Forecasting Analysis	65
5.4.9	Oct-2006 Load Forecasting Analysis	66
5.4.10	Oct-2007 Load Forecasting Analysis	67
5.4.11	Nov-2007 Load Forecasting Analysis	67
5.4.12	Dec-2007 Load Forecasting Analysis	68
5.4.13	Jan-2008 Load Forecasting Analysis	69
5.4.14	March-2008 Load Forecasting Analysis	69
5.4.15	May-2008 Load Forecasting Analysis	70
5.5	Hourly Load Forecasting Analysis	71
5.5.1	1-Oct-2007 Load Forecasting Analysis	71
5.5.2	2-Oct-2007 Load Forecasting Analysis	71
5.5.3	3-Oct-2007 Load Forecasting Analysis	72
5.5.4	4-Oct-2007 Load Forecasting Analysis	72
5.5.5	5-Oct-2007 Load Forecasting Analysis	73
5.5.6	6-Oct-2007 Load Forecasting Analysis	73
5.5.7	7-Oct-2007 Load Forecasting Analysis	74
5.5.8	Week-1 Oct-2007 Load Forecasting Analysis	74
5.5.9	8-Nov-2007 Load Forecasting Analysis	75
5.5.10	9-Nov-2007 Load Forecasting Analysis	75
5.5.11	10-Nov-2007 Load Forecasting Analysis	76
5.5.12	11-Nov-2007 Load Forecasting Analysis	76
5.5.13	12-Nov-2007 Load Forecasting Analysis	77
5.5.14	13-Nov-2007 Load Forecasting Analysis	77
5.5.15	14-Nov-2007 Load Forecasting Analysis	78
5.5.16	Week-2 Nov-2007 Load Forecasting Analysis	78
5.5.17	1-Jan-2008 Load Forecasting Analysis	79
5.5.18	2-Jan-2008 Load Forecasting Analysis	79
5.5.19	3-Jan-2008 Load Forecasting Analysis	80

5.5.20	4-Jan-2008 Load Forecasting Analysis	80
5.5.21	5-Jan-2008 Load Forecasting Analysis	81
5.5.22	6-Jan-2008 Load Forecasting Analysis	81
5.5.23	7-Jan-2008 Load Forecasting Analysis	82
5.5.24	Week-1 Jan-2008 Load Forecasting Analysis	82
5.5.25	1-June-2008 Load Forecasting Analysis	83
5.5.26	2-June-2008 Load Forecasting Analysis	83
5.5.27	3-June-2008 Load Forecasting Analysis	84
5.5.28	4-June-2008 Load Forecasting Analysis	84
5.5.29	5-June-2008 Load Forecasting Analysis	85
5.5.30	6-June-2008 Load Forecasting Analysis	85
5.5.31	7-June-2008 Load Forecasting Analysis	86
5.5.32	Week-1 June-2008 Load Forecasting Analysis	86
5.6	Multiple Linear Regression Model	87
5.6.1	Hourly Load Forecasting Analysis for First Week of June-2008	88
5.6.1.1	1-June-2008 Load Forecasting Regression Analysis	88
5.6.1.2	2-June-2008 Load Forecasting Regression Analysis	88
5.6.1.3	3-June-2008 Load Forecasting Regression Analysis	89
5.6.1.4	4-June-2008 Load Forecasting Regression Analysis	89
5.6.1.5	5-June-2008 Load Forecasting Regression Analysis	90
5.6.1.6	6-June-2008 Load Forecasting Regression Analysis	90
5.6.1.7	7-June-2008 Load Forecasting Regression Analysis	91
5.6.1.8	Week-1 June-2008 Load Forecasting Regression Analysis	91
5.7	Summary	92

<b>CHAPTER 6</b>	<b>CONCLUSION AND RECOMMENDATION</b>	<b>93</b>
6.1	Conclusion	93
6.2	Suggestion for Future Work	94
<b>REFERENCES</b>		<b>95</b>
<b>Appendices A - K</b>		<b>99 - 115</b>

## LIST OF TABLES

<b>TABLE NO.</b>	<b>TITLE</b>	<b>PAGE</b>
Table 2.1:	Classification of Load forecasting	13
Table 2.2:	Classification of Load Forecasting Techniques by Time Period, Influencing Factors, and Applications	15
Table 3.1:	Research Design Matrix	38
Table 3.2:	Research Design Time Line	38

## LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2.1:	Classification of Electric Load Forecasting	12
Figure 2.2:	The log sigmoid transfer function	20
Figure 2.3:	Pure transfer function of linear shape	20
Figure 2.4:	The tan sigmoid transfer function	20
Figure 3.1:	Block diagram for short term load forecasting	27
Figure 3.2:	Example of Hour of Day Demand in GW	28
Figure 3.3:	Example of Hour of Day Demand in GW	28
Figure 3.4:	Methodology Flow Chart	29
Figure 3.5:	Load profile Curve from Jan-2004 to June-2008	30
Figure 3.6:	Year 2005 Load Profile Curve	30
Figure 3.7:	Jan-2004 Load Profile Curve	31
Figure 3.8:	Jan-2004 Weak-1 Load Profile Curve	31
Figure 3.9:	Selected days for Load Profile Curve	31
Figure 3.10:	Load vs Temp from Jan-2004 to June-2008 Correlation	32
Figure 3.11:	1-Year Load vs Temperature Correlation	32
Figure 3.12:	1-Month Load vs Temperature Correlation	33
Figure 3.13:	1-Weak Load vs Temperature Correlation	33
Figure 3.14:	Selected Days for Load vs Temperature Correlation	33
Figure 4.1:	Steps of Training Back-Propagation ANN [35]	39
Figure 4.2:	<i>Multi-Layer Fed Forward Network</i> [36]	40
Figure 4.3:	Multilayer perceptron of neural network [38]	41
Figure 4.4:	Back Propagation Algorithm Flow Chart	45
Figure 5.1:	Schematic Structure of NN Model	47

Figure 5.2: MATLAB NN toolbox during the training phase of our MLP model	49
Figure 5.3: All Data: Actual vs Forecasted Load, Correlation between input and output, MSE & RMSE and Error Histogram	49
Figure 5.4: Training Data: Actual vs Forecasted Load, Correlation between input and output, MSE & RMSE and Error Histogram	49
Figure 5.5: Validation Data: Actual vs Forecasted Load, Correlation between input and output, MSE & RMSE and Error Histogram	50
Figure 5.6: Testing Data: Actual vs Forecasted Load, Correlation between input and output, MSE & RMSE and Error Histogram	51
Figure 5.7: NN Toolbox Regression plots of the MLP Model	52
Figure 5.8: NN Toolbox Performance function of our MLP Model	52
Figure 5.9: NN Toolbox Training state plot of MLP Model	53
Figure 5.10: Error Distribution Histogram for Training, Validation, and Testing Data	54
Figure 5.11: Actual vs Forecasted Load for All Data	54
Figure 5.12: Plot Show Errors in Graphical Form	55
Figure 5.13: Error Distribution, MAE and MAPE	55
Figure 5.14: 2004 Load Forecasting Analysis	56
Figure 5.15: 2004 Load Forecasting Analysis Error	56
Figure 5.16: 2005 Load Forecasting Analysis	57
Figure 5.17: 2005 Load Forecasting Analysis Error	57
Figure 5.18: 2006 Load Forecasting Analysis	58
Figure 5.19: 2006 Load Forecasting Analysis Error	58
Figure 5.20: 2007 Load Forecasting Analysis	59
Figure 5.21: 2007 Load Forecasting Analysis Error	59
Figure 5.22: 2008 Load Forecasting Analysis	60
Figure 5.23: 2008 Load Forecasting Analysis Error	60
Figure 5.24: Feb-2004 Load Forecasting Analysis	61
Figure 5.25: Feb-2004 Load Forecasting Analysis Error	61
Figure 5.26: March-2004 Load Forecasting Analysis	61

Figure 5.27: March-2004 Load Forecasting Analysis Error	62
Figure 5.28: April-2004 Load Forecasting Analysis	62
Figure 5.29: April-2004 Load Forecasting Analysis Error	62
Figure 5.30: April-2005 Load Forecasting Analysis	63
Figure 5.31: April-2005 Load Forecasting Analysis Error	63
Figure 5.32: May-2005 Load Forecasting Analysis	63
Figure 5.33: May-2005 Load Forecasting Analysis Error	64
Figure 5.34: Aug-2005 Load Forecasting Analysis	64
Figure 5.35: Aug-2005 Load Forecasting Analysis Error	64
Figure 5.36: July-2006 Load Forecasting Analysis	65
Figure 5.37: July-2006 Load Forecasting Analysis Error	65
Figure 5.38: Sep-2006 Load Forecasting Analysis	65
Figure 5.39: Sep-2006 Load Forecasting Analysis Error	66
Figure 5.40: Oct-2006 Load Forecasting Analysis	66
Figure 5.41: Oct-2006 Load Forecasting Analysis Error	66
Figure 5.42: Oct-2007 Load Forecasting Analysis	67
Figure 5.43: Oct-2007 Load Forecasting Analysis Error	67
Figure 5.44: Nov-2007 Load Forecasting Analysis	67
Figure 5.45: Nov-2007 Load Forecasting Analysis Error	68
Figure 5.46: Dec-2007 Load Forecasting Analysis	68
Figure 5.47: Dec-2007 Load Forecasting Analysis Error	68
Figure 5.48: Jan-2008 Load Forecasting Analysis	69
Figure 5.49: Jan-2008 Load Forecasting Analysis Error	69
Figure 5.50: March-2008 Load Forecasting Analysis	69
Figure 5.51: March-2008 Load Forecasting Analysis Error	70
Figure 5.52: May-2008 Load Forecasting Analysis	70
Figure 5.53: May-2008 Load Forecasting Analysis Error	70
Figure 5.54: 1-Oct-2007 Load Forecasting Analysis	71
Figure 5.55: 2-Oct-2007 Load Forecasting Analysis	71

Figure 5.56: 3-Oct-2007 Load Forecasting Analysis	72
Figure 5.57: 4-Oct-2007 Load Forecasting Analysis	72
Figure 5.58: 5-Oct-2007 Load Forecasting Analysis	73
Figure 5.59: 6-Oct-2007 Load Forecasting Analysis	73
Figure 5.60: 7-Oct-2007 Load Forecasting Analysis	74
Figure 5.61: Week-1 Oct-2007 Load Forecasting Analysis	74
Figure 5.62: 8-Nov-2007 Load Forecasting Analysis	75
Figure 5.63: 9-Nov-2007 Load Forecasting Analysis	75
Figure 5.64: 10-Nov-2007 Load Forecasting Analysis	76
Figure 5.65: 11-Nov-2007 Load Forecasting Analysis	76
Figure 5.66: 12-Nov-2007 Load Forecasting Analysis	77
Figure 5.67: 13-Nov-2007 Load Forecasting Analysis	77
Figure 5.68: 14-Nov-2007 Load Forecasting Analysis	78
Figure 5.69: Week-2 Nov-2007 Load Forecasting Analysis	78
Figure 5.70: 1-Jan-2008 Load Forecasting Analysis	79
Figure 5.71: 2-Jan-2008 Load Forecasting Analysis	79
Figure 5.72: 3-Jan-2008 Load Forecasting Analysis	80
Figure 5.73: 4-Jan-2008 Load Forecasting Analysis	80
Figure 5.74: 5-Jan-2008 Load Forecasting Analysis	81
Figure 5.75: 6-Jan-2008 Load Forecasting Analysis	81
Figure 5.76: 7-Jan-2008 Load Forecasting Analysis	82
Figure 5.77: Week-1 Jan-2008 Load Forecasting Analysis	82
Figure 5.78: 1-June-2008 Load Forecasting Analysis	83
Figure 5.79: 2-June-2008 Load Forecasting Analysis	83
Figure 5.80: 3-June-2008 Load Forecasting Analysis	84
Figure 5.81: 4-June-2008 Load Forecasting Analysis	84
Figure 5.82: 5-June-2008 Load Forecasting Analysis	85
Figure 5.83: 6-June-2008 Load Forecasting Analysis	85
Figure 5.84: 7-June-2008 Load Forecasting Analysis	86



Figure 5.85: Week-1 June-2008 Load Forecasting Analysis	86
Figure 5.86: Actual vs Forecasted Load for Multiple Linear Regression Model	87
Figure 5.87: Multiple Linear Regression Model Error	87
Figure 5.88: 1-June-2008 Load Forecasting Regression Analysis	88
Figure 5.89: 2-June-2008 Load Forecasting Regression Analysis	88
Figure 5.90: 3-June-2008 Load Forecasting Regression Analysis	89
Figure 5.91: 4-June-2008 Load Forecasting Regression Analysis	89
Figure 5.92: 5-June-2008 Load Forecasting Regression Analysis	90
Figure 5.93: 6-June-2008 Load Forecasting Regression Analysis	90
Figure 5.94: 7-June-2008 Load Forecasting Regression Analysis	91
Figure 5.95: Week-1 June-2008 Load Forecasting Regression Analysis	91

## 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

## LIST OF APPENDICES

<b>APPENDIX</b>	<b>TITLE</b>	<b>PAGE</b>
Appendix A:	Week-1 Oct-2007 AL, FL and APE of Hourly Load Forecasting Analysis	99
Appendix B:	Week-2 Nov-2007 AL, FL and APE of Hourly Load Forecasting Analysis	101
Appendix C:	Week-1 Jan-2008 AL, FL and APE of Hourly Load Forecasting Analysis	103
Appendix D:	Week-1 June-2008 (Neural Network) AL, FL and APE of Hourly Load Forecasting Analysis	105
Appendix E:	Week-1 June-2008 (ML Regression Model) AL, FL and APE of Hourly Load Forecasting Analysis	107
Appendix F:	Total Years 2004-June/2008 Forecasted Load Errors	109
Appendix G:	Selected Monthly Forecasted Load Errors	109
Appendix H:	Selected Daily Load Forecasted Errors	110
Appendix I:	Main Code	112
Appendix J:	Function Predictors	115
Appendix K:	Function Plot Results	115

# 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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