

A NOVEL ARCHITECTURE FOR ELECTRIC POWER LOAD FORECASTING IN A SMART GRID ENVIRONMENT

M.VETRI SELVI



**DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY DELHI
OCTOBER 2021**

© Indian Institute of Technology Delhi (IITD), New Delhi, 2021

A NOVEL ARCHITECTURE FOR ELECTRIC POWER LOAD FORECASTING IN A SMART GRID ENVIRONMENT

by

M.VETRI SELVI

Department of Electrical Engineering

Submitted

in fulfillment of the requirements of the degree of Doctor of Philosophy

to the



INDIAN INSTITUTE OF TECHNOLOGY DELHI

OCTOBER 2021

CERTIFICATE

This is to certify that the thesis entitled “**A Novel Architecture for Electric Power Load Forecasting in a Smart Grid Environment**”, submitted by **Mrs. M. Vetri Selvi**, to the Indian Institute of Technology, Delhi, is worthy of consideration for the award of the degree of **Doctor of Philosophy** and is a record of bonafide research work carried out by her. She has worked under my supervision and guidance and has fulfilled the requirements for the submission of this thesis. To the best of my knowledge, the results contained in this thesis have not been submitted elsewhere in part or full for the award of any degree or diploma.

Prof. Sukumar Mishra

Electrical Engineering Department
Indian Institute of Technology, Delhi
New Delhi – 110016, India

ACKNOWLEDGEMENTS

The journey for Ph. D degree is a culmination of discovery, desperation, joy, frustration, loneliness and delight. I feel blessed to see through this amazing journey with the support of colleagues, comrades and family. First and foremost, I would like to thank my supervisor **Prof. Sukumar Mishra** who have always provided constant support and motivation. He has taught me the importance of focus, scientific rigour and dedication needed for research study. I owe him a lot and I thank him for all the help that was rendered to me for my pursuit. He has also been providing relentless encouragement and inspiration throughout the duration of my study with his immense knowledge. Had it not been for his vision, support and his confidence in my learning, this work would not have been completed. I am deeply grateful to him for his time and invaluable inputs for my study.

Let me also take this opportunity to thank my central research committee: **Prof. Bhim Singh Prof. G. Bhuvaneswari, Prof. Nilanjan Senroy** and **Dr. Ashu Verma** for their valuable comments and suggestions on the dissertation. I would also like to express my sincere gratitude to the Head of Department, Electrical Engineering, **Prof. Jayadeva** for the supporting environment extended to me for the research.

I feel privileged to having worked along with many brilliant colleagues in our research group. The lab environment has always been encouraging and the conversations between Dr. Zarina, Dr. Gayathri, Dr.Sunitha Anup and T. Sathyanarayanan helped to work towards the culmination of the dissertation with hard work.

I am also grateful to **Mr. Dev Anand**, General Manager, **Mr. Goswamy**, Manager, **Mrs. Sujatha**, Manager, Tata Power Delhi Distribution Limited., for their complete support in providing necessary data for carrying out this research work successfully.

I am grateful to **Dr. George Varkey**, Scientist 'F', Former Executive Director, Centre for Development of Advanced Computing (CDAC), Noida through his inspiration and encouragement for the opportunity provided to pursue higher study. I am also thankful to **Mr. Vijayagopalan**, Scientist 'F'(Retired), CDAC, Noida for his constant support throughout the entire study.

I also extend my gratefulness to **Mr. E. Magesh**, Scientist 'F', Executive Director, CDAC, Thiruvananthapuram for the supporting environment extended to me for the research. I am also happy to express my thankfulness to **Mr. Renji V Chacko**, Scientist 'G', Group Head, PEG, **Mr. K.N. Mohanan**, Scientist 'E', former Section Head (Retired), P&S and **Mr. Jinuraj**, Scientist 'E', Section Head, P&S, CDAC, Thiruvananthapuram for their support to complete the study.

Last but not the least, I would like to thank my father K.Muniyandi and my mother M.Seethai whose love and guidance are with me whatever I pursue. I also wish to thank my loving husband G. Senthil Kumar have been a source of inspiration and resolute pillar through thick and thin. He has already taken a road to heaven before I complete this thesis work. Most importantly, I wish to thank my dear loving and wonderful sons V.S. Aadidev and V.S. Haridev who provide unending inspiration.

Date: 21.07.2021

M.Vetri Selvi

ABSTRACT

In a liberalized deregulated environment, Electric Power Load Forecasting (EPLF) is an important process in any power system network to make it an efficient, secure and consumer friendly electric power distribution utility. Electric power load increases tremendously especially for a Metropolitan city like Delhi due to climatic conditions, population growth, local area development, industries expansion, air pollution, thermal devices usage, etc. Hence, the accuracy of electric power load forecasting is a deciding factor for the electric power distribution utility to retain as an efficient and consumer friendly network. The proposed day-ahead EPLF models are built on a new multiple parallel inputs and output architecture with selected calendar, weather, smart grid factors and lagged electric load power features. This dissertation is mainly focused to deal with the selection and identification of best suitable features for creation of new architecture for EPLF model. The correlation analysis of EPL with respect to each selected feature is performed and presented. It also deliberates the implementation of RReliefF algorithm for selection and ranking of input features required for EPLF model. The real time data used for this research work were collected from Tata Power Delhi Distribution Limited (TPDDL). The EPLF models are developed using seven different techniques i.e: Multi-variate linear regression (MvLR) and Feed-forward neural network(FFNN), Cascade forward neural network(CFNN), Function fitting neural network(FFitNN), Layer Recurrent neural network(LRcNN), Standard LSTM deep learning network and Sequence-to-Sequence Regression LSTM deep learning network technique which are developed and implemented using MATLAB programming environment. The evaluation criteria for EPLF are presented with determination of various statistical errors. The performance of each model is analyzed and the results are presented with different techniques. As per the manner of usage of historical data, many methods have been proposed to study the performance of EPLF models. The performance of EPLF models are tested for different weather forecast errors. The proposed day-ahead ELPF models are evident for its simplicity, less measurement requirement and easiness in implementation with higher accuracy.

सार

एक उदारीकृत विनियंत्रित वातावरण में, इलेक्ट्रिक पावर लोड फोरकास्टिंग (ईपीएलएफ) किसी भी पावर सिस्टम नेटवर्क में इसे एक कुशल, सुरक्षित और उपभोक्ता अनुकूल बिजली वितरण उपयोगिता बनाने के लिए एक महत्वपूर्ण प्रक्रिया है। विशेष रूप से जलवायु परिस्थितियों, जनसंख्या वृद्धि, स्थानीय क्षेत्र के विकास, उद्योगों के विस्तार, वायु प्रदूषण, थर्मल उपकरणों के उपयोग आदि के कारण दिल्ली जैसे महानगरीय शहर के लिए बिजली का भार काफी बढ़ जाता है। इसलिए, बिजली के भार के पूर्वानुमान की सटीकता एक निर्णायक कारक है एक कुशल और उपभोक्ता अनुकूल नेटवर्क के रूप में बनाए रखने के लिए विद्युत बिजली वितरण उपयोगिता। प्रस्तावित ईपीएलएफ मॉडल नए मल्टीपल समानांतर इनपुट और आउटपुट आर्किटेक्चर पर चयनित कैलेंडर, मौसम, स्मार्ट ग्रिड कारकों और लैग्ड इलेक्ट्रिक लोड पावर सुविधाओं के साथ बनाए गए हैं। यह शोध प्रबंध मुख्य रूप से ईपीएलएफ मॉडल के लिए नई वास्तुकला के निर्माण के लिए सर्वोत्तम उपयुक्त विशेषताओं के चयन और पहचान पर केंद्रित है। प्रत्येक चयनित विशेषता के संबंध में ईपीएल का सहसंबंध विश्लेषण किया जाता है और प्रस्तुत किया जाता है। यह ईपीएलएफ मॉडल के लिए आवश्यक इनपुट सुविधाओं के चयन और रैंकिंग के लिए आररिलीफ एल्गोरिदम के कार्यान्वयन पर भी विचार-विमर्श करता है। इस शोध कार्य के लिए उपयोग किए गए रीयल टाइम डेटा टाटा पावर दिल्ली डिस्ट्रीब्यूशन लिमिटेड (टीपीडीडीएल) से एकत्र किए गए थे। ईपीएलएफ मॉडल सात अलग-अलग तकनीकों का उपयोग करके विकसित किए गए हैं जैसे: मल्टी-वेरिएट लीनियर रिग्रेशन (एमवीएलआर) और फीड-फॉरवर्ड न्यूरल नेटवर्क (एफएफएनएन), कैस्केड फॉरवर्ड न्यूरल नेटवर्क (सीएफएनएन), फंक्शन फिटिंग न्यूरल नेटवर्क (एफएफआईटीएनएन), लेयर रिकरंट न्यूरल नेटवर्क (LRcNN), स्टैंडर्ड LSTM डीप लर्निंग नेटवर्क और सीक्वेंस-टू-सीक्वेंस रिग्रेशन LSTM डीप लर्निंग नेटवर्क तकनीक जो MATLAB प्रोग्रामिंग वातावरण का उपयोग करके विकसित और कार्यान्वित की जाती हैं। ईपीएलएफ के लिए मूल्यांकन मानदंड विभिन्न सांख्यिकीय त्रुटियों के निर्धारण के साथ प्रस्तुत किए जाते हैं। प्रत्येक मॉडल के प्रदर्शन का विश्लेषण किया जाता है और परिणाम विभिन्न तकनीकों के साथ प्रस्तुत किए जाते हैं। ऐतिहासिक डेटा के उपयोग के तरीके के अनुसार, ईपीएलएफ मॉडल के प्रदर्शन का अध्ययन करने के लिए कई तरीके प्रस्तावित किए गए हैं। विभिन्न मौसम पूर्वानुमान त्रुटियों के लिए ईपीएलएफ मॉडल के प्रदर्शन का परीक्षण किया जाता है। प्रस्तावित दिन-आगे ईपीएलएफ मॉडल इसकी सादगी, कम माप की आवश्यकता और उच्च सटीकता के साथ कार्यान्वयन में आसानी के लिए स्पष्ट हैं।

CONTENTS

CERTIFICATE	i
ACKNOWLEDGEMENTS	iii
ABSTRACT	v
ABSTRACT IN HINDI	vi
CONTENTS	vii
LIST OF FIGURES	xxii
LIST OF TABLES	xlix
LIST OF ABBREVIATIONS	lv
CHAPTER 1	1
INTRODUCTION	1
1.1 Background of Electric Power Load Forecasting	1
1.1.1 Business Needs of EPLF	2
1.1.2 Classification of EPLF	3
1.1.3 Factors Influencing the EPLF	4
1.1.4 Advantages and Disadvantages of EPLF	5
1.2 Literature Review	6
1.3 Research Objectives of this Thesis work	9
1.4 EPLF Process for Model Development and Testing	10

1.4.1	EPLF Performance Evaluation Criteria	11
1.5	Hardware and Software Requirement for EPLF Model Development and Testing	12
1.6	Organization of Thesis	12
1.7	Major Contributions of the Thesis	14
1.8	Conclusion	15
	CHAPTER 2	16
	DATA ANALYSIS	16
2.1	Introduction	16
2.2	Data Pre-processing	16
2.2.1	Typical Pattern and causes of Bad data	16
2.2.2	Identification of Outliers/Bad data and Substituion of it	18
2.2.3	Identification of Missing Data and Substituion of it	18
2.3	Data Normalization	18
2.4	Data Characteristics Analysis	19
2.5	Conclusion	23
	CHAPTER 3	24
	FRAMING OF NEW ARCHITECTURE, SELECTION OF INPUT FEATURES AND RANKING ANALYSIS	24
3.1	Introduction	24
3.2	New Architecture chosen for EPLF Model Development	24
3.3	Correlation Analysis	25

3.3.1	Theoretical Background of Pearson Correlation Method	26
3.3.2	Development and Implementation of PC Method	27
3.4.	Filter Method for Feature Selection and Ranking Analysis	31
3.4.1	Theoretical Background of RReliefF Algorithm	32
3.4.2	Development and Implementation of RReliefF Method	33
3.5	Conclusion	36
CHAPTER 4		37
SELECTION, DEVELOPMENT AND IMPLEMENTATION OF DIFFERENT		37
TECHNIQUES		
4.1	Introduction	37
4.2	Theoretical Background of Selected Techniques	38
4.2.1	Multi-variate Linear Regression(MvLR) Technique	38
4.2.2	Feed-forward Neural Network(FFNN) Technique	39
4.2.3	Cascade Forward Neural Network(CFNN) Technique	40
4.2.4	Function Fitting Neural Network(FFitNN) Technique	40
4.2.5	Layer Recurrent Neural Network (LRcNN) Technique	40
4.2.6	Standard LSTM Deep Learning Network (LSTM) Technique	41
4.2.7	Sequence-to-Sequence Regression LSTM Deep Learning Network (S2S LSTM) Technique	45
4.3	Development and Implementation of Selected Techniques	49
4.3.1	Development and Implementation of MvLR Technique	50
4.3.2	Development and Implementation of Artificial Neural Network(ANN)	50

4.3.3	Development and Implementation of Standard LSTM Deep Learning Network Technique	51
4.3.4	Development and Implementation of Sequenc-to-Sequence Regression LSTM Deep Learning Network Technique	52
4.4	Results and Analysis of Selected Techniques	53
4.4.1	Results and Analysis of Multi-variate Linear Regression Technique	53
4.4.2	Results and Analysis of Feed-forward Neural Network Technique	57
4.4.3	Results and Analysis of Cascade Forward Neural Network Technique	60
4.4.4	Results and Analysis of Function Fitting Neural Network Technique	63
4.4.5	Results and Analysis of Layer Recurrent Neural Network Technique	66
4.4.6	Results and Analysis of Standard LSTM Deep Learning Network Technique	69
4.4.7	Results and Analysis of Sequence-to-Sequence Regression LSTM Deep Learning Network Technique	72
4.4.8	Comparative Analysis of All the Techniques developed	75
4.5	Conclusion	81
	CHAPTER 5	83
	STUDY AND ANALYSES OF IMPACT OF USAGE OF HISTORICAL DATA ON THE PERFORMANCE OF EPLF	83
5.1	Introduction	83
5.2	Development and Implementation of EPLF Model with Similar Day(SD) Method	83

5.3	Results and Analysis of EPLF Model with Similar Day Method	84
5.3.1	Results and Analysis of Similar Day Method using Multi-variate Linear Regression Technique	84
5.3.2	Results and Analysis of Similar Day Method using Feed-forward Neural Network Technique	86
5.3.3	Results and Analysis of Similar Day Method using Cascade Forward Neural Network Technique	87
5.3.4	Results and Analysis of Similar Day Method using Function Fitting Neural Network Technique	89
5.3.5	Results and Analysis of Similar Day Method using Layer Recurrent Neural Network Technique	90
5.3.6	Results and Analysis of Similar Day Method using Standard LSTM Deep Learning Network Technique	92
5.3.7	Results and Analysis of Similar Day Method using Sequence-to-Sequence Regression LSTM Deep Learning Network Technique	93
5.3.8	Comparative Analysis of All the Techniques developed in Similar Day Method	95
5.4	Development and Implementation of EPLF Model with Similar Month(SM) Method	101
5.5	Results and Analysis of EPLF Model with Similar Month Method	101
5.5.1	Results and Analysis of Similar Month Method using Multi-variate Linear Regression Technique	101

5.5.2	Results and Analysis of Similar Month Method using Feed-forward Neural Network Technique	103
5.5.3	Results and Analysis of Similar Month Method using Cascade Forward Neural Network Technique	105
5.5.4	Results and Analysis of Similar Month Method using Function Fitting Neural Network Technique	106
5.5.5	Results and Analysis of Similar Month Method using Layer Recurrent Neural Network Technique	108
5.5.6	Results and Analysis of Similar Month Method using Standard LSTM Deep Learning Network Technique	110
5.5.7	Results and Analysis of Similar Month Method using Sequence-to- Sequence Regression LSTM Deep Learning Network Technique	111
5.5.8	Comparative Analysis of All the Techniques developed in Similar Month Method	113
5.6	Development and Implementation of EPLF Model with Special Day Method	119
5.7	Results and Analysis of EPLF Model with Special Day Method	119
5.7.1	Results and Analysis of Special Day Method using Multi-variate Linear Regression Technique	119
5.7.2	Results and Analysis of Special Day Method using Feed-forward Neural Network Technique	121

5.7.3	Results and Analysis of Special Day Method using Cascade Forward Neural Network Technique	123
5.7.4	Results and Analysis of Special Day Method using Function Fitting Neural Network Technique	124
5.7.5	Results and Analysis of Special Day Method using Layer Recurrent Neural Network Technique	126
5.7.6	Results and Analysis of Special Day Method using Standard LSTM Deep Learning Network Technique	128
5.7.7	Results and Analysis of Special Day Method using Sequence-to- Sequence Regression LSTM Deep Learning Network Technique	129
5.7.8	Comparative Analysis of All the Techniques developed in Special Day Method	131
5.8	Development and Implementation of EPLF Model with Greater Number of Years Method	136
5.9	Results and Analysis of EPLF Model with Greater Number of Years Method	137
5.9.1	Results and Analysis of Greater Number of Years Method using Multi- variate Linear Regression Technique	137
5.9.2	Results and Analysis of Greater Number of Years Method using Feed- forward Neural Network Technique	139
5.9.3	Results and Analysis of Greater Number of Years Method using Cascade Forward Neural Network Technique	140

5.9.4	Results and Analysis of Greater Number of Years Method using Function Fitting Neural Network Technique	141
5.9.5	Results and Analysis of Greater Number of Years Method using Layer Recurrent Neural Network Technique	142
5.9.6	Results and Analysis of Greater Number of Years Method using Standard LSTM Deep Learning Network Technique	143
5.9.7	Results and Analysis of Greater Number of Years Method using Sequence-to-Sequence Regression LSTM Deep Learning Network Technique	144
5.9.8	Comparative Analysis of All the Techniques developed in Greater Number of Years Method	145
5.10	Conclusion	150
	CHAPTER 6	152
	STUDY AND ANALYSES OF IMPACT OF VARIOUS INPUT FEATURES ON THE PERFORMANCE OF EPLF	152
6.1	Introduction	152
6.2	Development and Implementation of EPLF Model without Calendar Features	152
6.3	Results and Analysis of EPLF Model without Calendar Features	153
6.3.1	Results and Analyses of Multi-variate Linear Regression Technique developed without Calendar Features	153

6.3.2	Results and Analyses of Feed-forward Neural Network Technique developed without Calendar Features	155
6.3.3	Results and Analyses of Cascade Forward Neural Network Technique developed without Calendar Features	156
6.3.4	Results and Analyses of Function Fitting Neural Network Technique developed without Calendar Features	158
6.3.5	Results and Analyses of Layer Recurrent Neural Network Technique developed without Calendar Features	159
6.3.6	Results and Analyses of Standard LSTM Deep Learning Network Technique developed without Calendar Features	161
6.3.7	Results and Analyses of Sequence-to-Sequence Regression LSTM Deep Learning Network Technique developed without Calendar Features	163
6.3.8	Comparative Analyses of All the Techniques developed without Calendar Features	164
6.4	Development and Implementation of EPLF Model without Weather Features	166
6.5	Results and Analysis of EPLF Model without Weather Features	167
6.5.1	Results and Analyses of Multi-variate Linear Regression Technique developed without Weather Features	167
6.5.2	Results and Analyses of Feed-forward Neural Network Technique developed without Weather Features	169

6.5.3	Results and Analyses of Cascade Forward Neural Network Technique developed without Weather Features	170
6.5.4	Results and Analyses of Function Fitting Neural Network Technique developed without Weather Features	172
6.5.5	Results and Analyses of Layer Recurrent Neural Network Technique developed without Weather Features	173
6.5.6	Results and Analyses of Standard LSTM Deep Learning Network Technique developed without Weather Features	175
6.5.7	Results and Analyses of Sequence-to-Sequence Regression LSTM Deep Learning Network Technique developed without Weather Features	177
6.5.8	Comparative Analyses of All the Techniques developed without Weather Features	178
6.6	Development and Implementation of EPLF Model without Smart grid Features	184
6.7	Results and Analysis of EPLF Model without Smart grid Features	184
6.7.1	Results and Analyses of Multi-variate Linear Regression Technique developed without Smart grid Features	185
6.7.2	Results and Analyses of Feed-forward Neural Network Technique developed without Smart grid Features	186
6.7.3	Results and Analyses of Cascade Forward Neural Network Technique developed without Smart grid Features	188

6.7.4	Results and Analyses of Function Fitting Neural Network Technique developed without Smart grid Features	190
6.7.5	Results and Analyses of Layer Recurrent Neural Network Technique developed without Smart grid Features	191
6.7.6	Results and Analyses of Standard LSTM Deep Learning Network Technique developed without Smart grid Features	193
6.7.7	Results and Analyses of Sequence-to-Sequence Regression LSTM Deep Learning Network Technique developed without Smart grid Features	195
6.7.8	Comparative Analyses of All the Techniques developed without Smart grid Features	196
6.8	Development and Implementation of EPLF Model with Temperature Forecast Errors	201
6.9	Results and Analysis of EPLF Model with Temperature Forecast Errors	202
6.9.1	Results and Analyses of Multi-variate Linear Regression Technique developed with Temperature Forecast Errors	202
6.9.2	Results and Analyses of Feed-forward Neural Network Technique developed with Temperature Forecast Errors	203
6.9.3	Results and Analyses of Cascade Forward Neural Network Technique developed with Temperature Forecast Errors	204
6.9.4	Results and Analyses of Function Fitting Neural Network Technique developed with Temperature Forecast Errors	205

6.9.5	Results and Analyses of Layer Recurrent Neural Network Technique developed with Temperature Forecast Errors	206
6.9.6	Results and Analyses of Standard LSTM Deep Learning Network Technique developed with Temperature Forecast Errors	207
6.9.7	Results and Analyses of Sequence-to-Sequence Regression LSTM Deep Learning Network Technique developed with Temperature Forecast Errors	208
6.9.8	Comparative Analyses of All the Techniques developed with Temperature Forecast Errors	209
6.10	Development and Implementation of EPLF Model with Relative Humidity Forecast Errors	212
6.11	Results and Analysis of EPLF Model with Relative Humidity Forecast Errors	213
6.11.1	Results and Analyses of Multi-variate Linear Regression Technique developed with Relative Humidity Forecast Errors	213
6.11.2	Results and Analyses of Feed-forward Neural Network Technique developed with Relative Humidity Forecast Errors	214
6.11.3	Results and Analyses of Cascade Forward Neural Network Technique developed with Relative Humidity Forecast Errors	215
6.11.4	Results and Analyses of Function Fitting Neural Network Technique developed with Relative Humidity Forecast Errors	216

6.11.5	Results and Analyses of Layer Recurrent Neural Network Technique developed with Relative Humidity Forecast Errors	217
6.11.6	Results and Analyses of Standard LSTM Deep Learning Network Technique developed with Relative Humidity Forecast Errors	218
6.11.7	Results and Analyses of Sequence-to-Sequence Regression LSTM Deep Learning Network Technique developed with Relative Humidity Forecast Errors	219
6.11.8	Comparative Analyses of All the Techniques developed with Relative Humidity Forecast Errors	220
6.12	Development and Implementation of EPLF Model with Wind Speed Forecast Errors	223
6.13	Results and Analysis of EPLF Model with Wind Speed Forecast Errors	224
6.13.1	Results and Analyses of Multi-variate Linear Regression Technique developed with Wind Speed Forecast Errors	224
6.13.2	Results and Analyses of Feed-forward Neural Network Technique developed with Wind Speed Forecast Errors	225
6.13.3	Results and Analyses of Cascade Forward Neural Network Technique developed with Wind Speed Forecast Errors	226
6.13.4	Results and Analyses of Function Fitting Neural Network Technique developed with Wind Speed Forecast Errors	227

6.13.5	Results and Analyses of Layer Recurrent Neural Network Technique developed with Wind Speed Forecast Errors	228
6.13.6	Results and Analyses of Standard LSTM Deep Learning Network Technique developed with Wind Speed Forecast Errors	229
6.13.7	Results and Analyses of Sequence-to-Sequence Regression LSTM Deep Learning Network Technique developed with Wind Speed Forecast Errors	230
6.13.8	Comparative Analyses of All the Techniques developed with Wind Speed Forecast Errors	231
6.14	Development and Implementation of EPLF Model with Weather Forecast Errors	234
6.15	Results and Analysis of EPLF Model with Weather Forecast Errors	235
6.15.1	Results and Analyses of Multi-variate Linear Regression Technique developed with Weather Forecast Errors	235
6.15.2	Results and Analyses of Feed-forward Neural Network Technique developed with Weather Forecast Errors	236
6.15.3	Results and Analyses of Cascade Forward Neural Network Technique developed with Weather Forecast Errors	237
6.15.4	Results and Analyses of Function Fitting Neural Network Technique developed with Weather Forecast Errors	238
6.15.5	Results and Analyses of Layer Recurrent Neural Network Technique developed with Weather Forecast Errors	239

6.15.6	Results and Analyses of Standard LSTM Deep Learning Network Technique developed with Weather Forecast Errors	240
6.15.7	Results and Analyses of Sequence-to-Sequence Regression LSTM Deep Learning Network Technique developed with Weather Forecast Errors	241
6.15.8	Comparative Analyses of All the Techniques developed with Weather Forecast Errors	242
6.16	Conclusion	245
	CHAPTER 7	248
	CONCLUSION	248
7.1	Summary of Conclusions	248
7.2	Suggestions for Future Work	250
	REFERENCES	252
	LIST OF PUBLICATIONS	258
	BIO-DATA	260

LIST OF FIGURES

Fig. 1.1. Processes involved in EPLF Model Development and Testing

Fig. 1.2. Organization of Thesis

Fig. 2.1. Summer first week ELP pattern variation in Delhi

Fig. 2.2. Average ELP demand variation on day of the week

Fig. 2.3. Average ELP demand on week day and week end

Fig. 2.4. Comparison of average ELP demand on special day and a normal day

Fig. 2.5. Variation of average ELP on Industries working/non-working days

Fig. 2.6. Seasonal variation of average ELP in the year 2016

Fig. 2.7. Every fifth Friday of each season ELP demand pattern variation in Delhi in the year 2016

Fig. 2.8. Seasonal variation of Average ELP demand with respect to average air temperature in year 2016

Fig. 2.9. Seasonal variation of average ELP demand with respect to average relative humidity in year 2016

Fig. 2.10. Seasonal variation of average ELP demand with respect to average wind speed in year 2016

Fig. 3.1. Block diagram representation of Architecture for EPLF Model Development

Fig. 3.2. Pearson correlation method-based correlation co-efficient obtained for each feature with respect to actual electric load power obtained on forecasted day

Fig. 3.3. Correlation co-efficient obtained for Season with respect to actual electric load power obtained on forecasted day

Fig. 3.4. Correlation co-efficient obtained for Month with respect to actual electric load power obtained on forecasted day

Fig. 3.5. Correlation co-efficient obtained for Day of the Week with respect to actual electric load power obtained on forecasted day

Fig. 3.6. Correlation co-efficient obtained for Weekend factor with respect to actual electric load power obtained on forecasted day

Fig. 3.7. Correlation co-efficient obtained for Holiday factor with respect to actual electric load power obtained on forecasted day

Fig. 3.8. Correlation co-efficient obtained for IndustryOFF factor with respect to actual electric load power obtained on forecasted day

Fig. 3.9. Correlation co-efficient obtained for Air Temperature with respect to actual electric load power obtained on forecasted day

Fig. 3.10. Correlation co-efficient obtained for Relative Humidity with respect to actual electric load power obtained on forecasted day

Fig. 3.11. Correlation co-efficient obtained for Wind Speed with respect to actual electric load power obtained on forecasted day

Fig. 3.12. Correlation co-efficient obtained for Previous Day Electric load power with respect to actual electric load power obtained on forecasted day

Fig. 3.13. Correlation co-efficient obtained for type of consumer with respect to actual electric load power obtained on forecasted day

Fig. 3.14. Correlation co-efficient obtained for type of tariff with respect to actual electric load power obtained on forecasted day

Fig. 3.15. RReliefF method-based weightage value obtained for each feature with respect to actual electric power load

Fig. 4.1. Block Diagram of LSTM Cell

Fig. 4.2. LSTM Architecture used for EPLF

Fig. 4.3. LSTM network to make predictions in an arbitrary number of future time steps

Fig. 4.4. Sequence-to-Sequence Regression Architecture

Fig. 4.5. Block Diagram Representation of New Architecture of EPLF Model developed

Fig. 4.6. Histogram chart of forecast error obtained in MvLR Technique

Fig. 4.7. Instantaneous samples of forecast error obtained in MvLR Technique

Fig. 4.8. Pie chart representation of obtained forecast error in MvLR Technique

Fig. 4.9. Daily Forecast Error obtained in MvLR Technique

Fig. 4.10. Daily MAPE obtained in MvLR Technique

Fig. 4.11. Daily MAE obtained in MvLR Technique

Fig. 4.12. Daily RMSE obtained in MvLR Technique

Fig. 4.13. Histogram chart of forecast error obtained in FFNN Technique

Fig. 4.14. Instantaneous samples of forecast error obtained in FFNN Technique

Fig. 4.15. Pie chart representation of obtained forecast error in FFNN Technique

Fig. 4.16. Daily Forecast Error obtained in FFNN Technique

Fig. 4.17. Daily MAPE obtained in FFNN Technique

Fig. 4.18. Daily MAE obtained in FFNN Technique

Fig. 4.19. Daily RMSE obtained in FFNN Technique

Fig. 4.20. Histogram chart of forecast error obtained in CFNN Technique

Fig. 4.21. Instantaneous samples of forecast error obtained in CFNN Technique

Fig. 4.22. Pie chart representation of obtained forecast error in CFNN Technique

Fig. 4.23. Daily Forecast Error obtained in CFNN Technique

Fig. 4.24. Daily MAPE obtained in CFNN Technique

Fig. 4.25. Daily MAE obtained in CFNN Technique

Fig. 4.26. Daily RMSE obtained in CFNN Technique

Fig. 4.27. Histogram chart of forecast error obtained in FFitNN Technique

Fig. 4.28. Instantaneous samples of forecast error obtained in FFitNN Technique

Fig. 4.29. Pie chart representation of obtained forecast error in FFitNN Technique

Fig. 4.30. Daily Forecast Error obtained in FFitNN Technique

Fig. 4.31. Daily MAPE obtained in FFitNN Technique

Fig. 4.32. Daily MAE obtained in FFitNN Technique

Fig. 4.33. Daily RMSE obtained in FFitNN Technique

Fig. 4.34. Histogram chart of forecast error obtained in LRcNN Technique

Fig. 4.35. Instantaneous samples of forecast error obtained in LRcNN Technique

Fig. 4.36. Pie chart representation of obtained forecast error in LRcNN Technique

Fig. 4.37. Daily Forecast Error obtained in LRcNN Technique

Fig. 4.38. Daily MAPE obtained in LRcNN Technique

Fig. 4.39. Daily MAE obtained in LRcNN Technique

Fig. 4.40. Daily RMSE obtained in LRcNN Technique

Fig. 4.41. Histogram chart of forecast error obtained in Standard LSTM Technique

Fig. 4.42. Instantaneous samples of forecast error obtained in Standard LSTM Technique

Fig. 4.43. Pie chart representation of obtained forecast error in Standard LSTM Technique

Fig. 4.44. Daily Forecast Error obtained in Standard LSTM Technique

Fig. 4.45. Daily MAPE obtained in Standard LSTM Technique

Fig. 4.46. Daily MAE obtained in Standard LSTM Technique

Fig. 4.47. Daily RMSE obtained in Standard LSTM Technique

Fig. 4.48. Histogram chart of forecast error obtained in S2S LSTM Technique

Fig. 4.49. Instantaneous samples of forecast error obtained in S2S LSTM Technique

Fig. 4.50. Pie chart representation of obtained forecast error in S2S LSTM Technique

Fig. 4.51. Daily Forecast Error obtained in S2S LSTM Technique

Fig. 4.52. Daily MAPE obtained in S2S LSTM Technique

Fig. 4.53. Daily MAE obtained in S2S LSTM Technique

Fig. 4.54. Daily RMSE obtained in S2S LSTM Technique

Fig. 4.55. Season wise forecast error obtained by each technique

Fig. 4.56. Month wise forecast error obtained by each technique

Fig. 4.57. Day of the Week wise forecast error obtained by each technique

Fig. 4.58. Weekend wise forecast error obtained by each technique

Fig. 4.59. Special day wise forecast error obtained by each technique

Fig. 4.60. IndustryOFF wise forecast error obtained by each technique

Fig. 4.61. Type of Consumer wise forecast error obtained by each technique

Fig. 4.62. Type of Tariff wise forecast error obtained by each technique

Fig. 4.63. Different Performance criteria obtained by each Technique

Fig. 5.1. Block Diagram Representation of Architecture of Model developed with Similar Day Method

Fig. 5.2 Instantaneous samples of obtained forecast error in MvLR Technique developed with Similar Day Method

Fig. 5.3. Pie chart of Forecast error in MvLR Technique developed with Similar Day Method

Fig. 5.4. Daily Forecast Error obtained in MvLR Technique developed with Similar Day Method

Fig. 5.5. Daily MAPE obtained in MvLR Technique developed with Similar Day Method

Fig. 5.6. Daily MAE obtained in MvLR Technique developed with Similar Day Method

Fig. 5.7. Daily RMSE obtained in MvLR Technique developed with Similar Day Method

Fig. 5.8. Instantaneous samples of obtained forecast error in FFNN Technique developed with Similar Day Method

Fig. 5.9. Pie chart of Forecast error in FFNN Technique developed with Similar Day Method

Fig. 5.10. Daily Forecast Error obtained in FFNN Technique developed with Similar Day Method

Fig. 5.11. Daily MAPE obtained in FFNN Technique developed with Similar Day Method

Fig. 5.12. Daily MAE obtained in FFNN Technique developed with Similar Day Method

Fig. 5.13. Daily RMSE obtained in FFNN Technique developed with Similar Day Method

Fig. 5.14 Instantaneous samples of obtained forecast error in CFNN Technique developed with Similar Day Method

Fig.5.15. Pie chart of Forecast error in CFNN Technique developed with Similar Day Method

Fig. 5.16. Daily Forecast Error obtained in CFNN Technique developed with Similar Day Method

Fig. 5.17. Daily MAPE obtained in CFNN Technique developed with Similar Day Method

Fig. 5.18. Daily MAE obtained in CFNN Technique developed with Similar Day Method

Fig. 5.19. Daily RMSE obtained in CFNN Technique developed with Similar Day Method

Fig. 5.20 Instantaneous samples of obtained forecast error in FFitNN Technique developed with Similar Day Method

Fig. 5.21. Pie chart of Forecast error in FFitNN Technique developed with Similar Day Method

Fig. 5.22. Daily Forecast Error obtained in FFitNN Technique developed with Similar Day Method

Fig. 5.23. Daily MAPE obtained in FFitNN Technique developed with Similar Day Method

Fig. 5.24. Daily MAE obtained in FFitNN Technique developed with Similar Day Method

Fig. 5.25. Daily RMSE obtained in FFitNN Technique developed with Similar Day Method

Fig. 5.26. Instantaneous samples of obtained forecast error in LRcNN Technique developed with Similar Day Method

Fig. 5.27. Pie chart of Forecast error in LRcNN Technique developed with Similar Day Method

Fig. 5.28. Daily Forecast Error obtained in LRcNN Technique developed with Similar Day Method

Fig. 5.29. Daily MAPE obtained in LRcNN Technique developed with Similar Day Method

Fig. 5.30. Daily MAE obtained in LRcNN Technique developed with Similar Day Method

Fig. 5.31. Daily RMSE obtained in LRcNN Technique developed with Similar Day Method

Fig. 5.32. Instantaneous samples of obtained forecast error in Standard LSTM Technique developed with Similar Day Method

Fig. 5.33. Pie chart of Forecast error in Standard LSTM Technique developed with Similar Day Method

Fig. 5.34. Daily Forecast Error obtained in Standard LSTM Technique developed with Similar Day Method

Fig. 5.35. Daily MAPE obtained in Standard LSTM Technique developed with Similar Day Method

Fig. 5.36. Daily MAE obtained in Standard LSTM Technique developed with Similar Day Method

Fig. 5.37. Daily RMSE obtained in Standard LSTM Technique developed with Similar Day Method

Fig. 5.38. Instantaneous samples of obtained forecast error in S2S LSTM Technique developed with Similar Day Method

Fig. 5.39. Pie chart of Forecast error in S2S LSTM Technique developed with Similar Day Method

Fig. 5.40. Daily Forecast Error obtained in S2S LSTM Technique developed with Similar Day Method

Fig. 5.41. Daily MAPE obtained in S2S LSTM Technique developed with Similar Day Method

Fig. 5.42. Daily MAE obtained in S2S LSTM Technique developed with Similar Day Method

Fig. 5.43. Daily RMSE obtained in S2S LSTM Technique developed with Similar Day Method

Fig. 5.44. Season wise forecast error obtained by each technique developed in Similar Day Method

Fig. 5.45. Month wise forecast error obtained in each technique developed in Similar Day Method

Fig. 5.46. Day of the Week wise forecast error obtained in each technique developed in Similar Day Method

Fig. 5.47. Weekend wise forecast error obtained in each technique developed in Similar Day Method

Fig. 5.48. Normal day/Special day wise forecast error obtained in each technique developed in Similar Day Method

Fig. 5.49. IndustryOFF wise forecast error obtained in each technique developed in Similar Day Method

Fig. 5.50. Type of Consumer wise forecast error obtained in each technique developed in Similar Day Method

Fig. 5.51. Type of Tariff wise forecast error obtained in each technique developed in Similar Day Method

Fig. 5.52. Different Performance criteria obtained in each Technique developed with Similar Day Method

Fig. 5.53. Block Diagram Representation of Architecture of Model developed with Similar Month Method

Fig. 5.54 Instantaneous samples of obtained forecast error in MvLR Technique developed with Similar Month Method

Fig. 5.55. Pie chart of Forecast error in MvLR Technique developed with Similar Month Method

Fig. 5.56. Daily Forecast Error obtained in MvLR Technique developed with Similar Month Method

Fig. 5.57. Daily MAPE obtained in MvLR Technique developed with Similar Month Method

Fig. 5.58. Daily MAE obtained in MvLR Technique developed with Similar Month Method

Fig. 5.59. Daily RMSE obtained in MvLR Technique developed with Similar Month Method

Fig. 5.60 Instantaneous samples of obtained forecast error in FFNN Technique developed with Similar Month Method

Fig. 5.61. Pie chart of Forecast error in FFNN Technique developed with Similar Month Method

Fig. 5.62. Daily Forecast Error obtained in FFNN Technique developed with Similar Month Method

Fig. 5.63. Daily MAPE obtained in FFNN Technique developed with Similar Month Method

Fig. 5.64. Daily MAE obtained in FFNN Technique developed with Similar Month Method

Fig. 5.65. Daily RMSE obtained in FFNN Technique developed with Similar Month Method

Fig. 5.66 Instantaneous samples of obtained forecast error in CFNN Technique developed with Similar Month Method

Fig.5.67. Pie chart of Forecast error in CFNN Technique developed with Similar Month Method

Fig. 5.68. Daily Forecast Error obtained in CFNN Technique developed with Similar Month Method

Fig. 5.69. Daily MAPE obtained in CFNN Technique developed with Similar Month Method

Fig. 5.70. Daily MAE obtained in CFNN Technique developed with Similar Month Method

Fig. 5.71. Daily RMSE obtained in CFNN Technique developed with Similar Month Method

Fig. 5.72 Instantaneous samples of obtained forecast error in FFitNN Technique developed with Similar Month Method

Fig. 5.73. Pie chart of Forecast error in FFitNN Technique developed with Similar Month Method

Fig. 5.74. Daily Forecast Error obtained in FFitNN Technique developed with Similar Month Method

Fig. 5.75. Daily MAPE obtained in FFitNN Technique developed with Similar Month Method

Fig. 5.76. Daily MAE obtained in FFitNN Technique developed with Similar Month Method

Fig. 5.77. Daily RMSE obtained in FFitNN Technique developed with Similar Month Method

Fig. 5.78. Instantaneous samples of obtained forecast error in LRcNN Technique developed with Similar Month Method

Fig. 5.79. Pie chart of Forecast error in LRcNN Technique developed with Similar Month Method

Fig. 5.80. Daily Forecast Error obtained in LRcNN Technique developed with Similar Month Method

Fig. 5.81. Daily MAPE obtained in LRcNN Technique developed with Similar Month Method

Fig. 5.82. Daily MAE obtained in LRcNN Technique developed with Similar Month Method

Fig. 5.83. Daily RMSE obtained in LRcNN Technique developed with Similar Month Method

Fig. 5.84. Instantaneous samples of obtained forecast error in Standard LSTM Technique developed with Similar Month Method

Fig. 5.85. Pie chart of Forecast error in Standard LSTM Technique developed with Similar Month Method

Fig. 5.86. Daily Forecast Error in Standard LSTM Technique developed with Similar Month Method

Fig. 5.87. Daily MAPE obtained in Standard LSTM Technique developed with Similar Month Method

Fig. 5.88. Daily MAE obtained in Standard LSTM Technique developed with Similar Month Method

Fig. 5.89. Daily RMSE obtained in Standard LSTM Technique developed with Similar Month Method

Fig. 5.90. Instantaneous samples of obtained forecast error by Sequence-to-Sequence Regression LSTM Technique developed with Similar Month Method

Fig. 5.91. Pie chart of Forecast error by Sequence-to-Sequence Regression LSTM Technique developed with Similar Month Method

Fig. 5.92. Daily Forecast Error by Sequence-to-Sequence Regression LSTM Technique developed with Similar Month Method

Fig. 5.93. Daily MAPE obtained by Sequence-to-Sequence Regression LSTM Technique developed with Similar Month Method

Fig. 5.94. Daily MAE obtained by Sequence-to-Sequence Regression LSTM Technique developed with Similar Month Method

Fig. 5.95. Daily RMSE obtained by Sequence-to-Sequence Regression LSTM Technique developed with Similar Month Method

Fig. 5.96. Season wise forecast error obtained in each technique developed with Similar Month Method

Fig. 5.97. Month wise forecast error obtained in each technique developed in Similar Month Method

Fig. 5.98. Day of the Week wise forecast error obtained in each technique developed in Similar Month Method

Fig. 5.99. Weekend wise forecast error obtained in each technique developed in Similar Month Method

Fig. 5.100. Special day wise forecast error obtained in each technique developed in Similar Month Method

Fig. 5.101. IndustryOFF wise forecast error obtained in each technique developed in Similar Month Method

Fig. 5.102. Type of Consumer wise forecast error obtained in each technique developed in Similar Month Method

Fig. 5.103. Type of Tariff wise forecast error obtained in each technique developed in Similar Month Method

Fig. 5.104. Different Performance criteria obtained by each Technique developed in Similar Month Method

Fig. 5.105. Block Diagram Representation of Architecture of EPLF Model developed with Special Day Method

Fig. 5.106. Instantaneous samples of obtained forecast error in MvLR Technique developed with Special Day Method

Fig. 5.107. Pie chart of Forecast error in MvLR Technique developed with Special Day Method

Fig. 5.108. Daily Forecast Error obtained in MvLR Technique developed with Special Day Method

Fig. 5.109. Daily MAPE obtained in MvLR Technique developed with Special Day Method

Fig. 5.110. Daily MAE obtained in MvLR Technique developed with Special Day Method

Fig. 5.111. Daily RMSE obtained in MvLR Technique developed with Special Day Method

Fig. 5.112. Instantaneous samples of obtained forecast error in FFNN Technique developed with Special Day Method

Fig. 5.113. Pie chart of Forecast error in FFNN Technique developed with Special Day Method

Fig. 5.114. Daily Forecast Error obtained in FFNN Technique developed with Special Day Method

Fig.5.115. Daily MAPE obtained in FFNN Technique developed with Special Day Method

Fig. 5.116. Daily MAE obtained in FFNN Technique developed with Special Day Method

Fig. 5.117. Daily RMSE obtained in FFNN Technique developed with Special Day Method

Fig. 5.118. Instantaneous samples of obtained forecast error in CFNN Technique developed with Special Day Method

Fig.5.119. Pie chart of Forecast error in CFNN Technique developed with Special Day Method

Fig. 5.120. Daily Forecast Error obtained in CFNN Technique developed with Special Day Method

Fig. 5.121. Daily MAPE obtained in CFNN Technique developed with Special Day Method

Fig. 5.122. Daily MAE obtained in CFNN Technique developed with Special Day Method

Fig. 5.123. Daily RMSE obtained in CFNN Technique developed with Special Day Method

Fig. 5.124. Instantaneous samples of obtained forecast error in FFitNN Technique developed with Special Day Method

Fig. 5.125. Pie chart of Forecast error in FFitNN Technique developed with Special Day Method

Fig. 5.126. Daily Forecast Error obtained in FFitNN Technique developed with Special Day Method

Fig. 5.127. Daily MAPE obtained in FFitNN Technique developed with Special Day Method

Fig. 5.128. Daily MAE obtained in FFitNN Technique developed with Special Day Method

Fig. 5.129. Daily RMSE obtained in FFitNN Technique developed with Special Day Method

Fig. 5.130. Instantaneous samples of obtained forecast error in LRcNN Technique developed with Special Day Method

Fig. 5.131. Pie chart of Forecast error in LRcNN Technique developed with Special Day Method

Fig. 5.132. Daily Forecast Error obtained in LRcNN Technique developed with Special Day Method

Fig. 5.133. Daily MAPE obtained in LRcNN Technique developed with Special Day Method

Fig. 5.134. Daily MAE obtained in LRcNN Technique developed with Special Day Method

Fig. 5.135. Daily RMSE obtained in LRcNN Technique developed with Special Day Method

Fig. 5.136. Instantaneous samples of obtained forecast error in Standard LSTM Technique developed with Special Day Method

Fig. 5.137. Pie chart of Forecast error in Standard LSTM Technique developed with Special Day Method

Fig. 5.138. Daily Forecast Error obtained in Standard LSTM Technique developed with Special Day Method

Fig. 5.139. Daily MAPE obtained in Standard LSTM Technique developed with Special Day Method

Fig. 5.140. Daily MAE obtained in Standard LSTM Technique developed with Special Day Method

Fig. 5.141. Daily RMSE obtained in Standard LSTM Technique developed with Special Day Method

Fig. 5.142. Instantaneous samples of obtained forecast error in S2S LSTM Technique developed with Special Day Method

Fig. 5.143. Pie chart of Forecast error in S2S LSTM Technique developed with Special Day Method

Fig. 5.144. Daily Forecast Error obtained in S2S LSTM Technique developed with Special Day Method

Fig. 5.145. Daily MAPE obtained in S2S LSTM Technique developed with Special Day Method

Fig. 5.146. Daily MAE obtained in S2S LSTM Technique developed with Special Day Method

Fig. 5.147. Daily RMSE obtained in S2S LSTM Technique developed with Special Day Method

Fig. 5.148. Season wise forecast error obtained in each technique with Special Day Method

Fig. 5.149. Month wise forecast error obtained in each technique with Special Day Method

Fig. 5.150. Day of the Week wise forecast error obtained in each technique with Special Day Method

Fig. 5.151. Weekend wise forecast error obtained in each technique with Special Day Method

Fig. 5.152. IndustryOFF wise forecast error obtained in each technique with Special Day Method

Fig. 5.153. Type of Consumer wise forecast error obtained in each technique with Special Day Method

Fig. 5.154. Type of Tariff wise forecast error obtained in each technique with Special Day Method

Fig. 5.155. Different Performance criteria obtained by each Technique in Special Day Method

Fig. 5.156. Block Diagram Representation of Architecture of EPLF Model developed

Fig. 5.157. Different Performance criteria obtained in MvLR Technique With Greater number of years Method

Fig. 5.158. Different Performance criteria obtained in FFNN Technique With Greater number of years Method

Fig. 5.159. Different Performance criteria obtained in CFNN Technique With Greater number of years Method

Fig. 5.160. Different Performance criteria obtained in FFitNN Technique With Greater number of years Method

Fig. 5.161. Different Performance criteria obtained in LRcNN Technique With Greater number of years Method

Fig. 5.162. Different Performance criteria obtained in Standard LSTM Technique With Greater number of years Method

Fig. 5.163. Different Performance criteria obtained in S2S LSTM Technique With Greater number of years Method

Fig. 5.164. Different Performance criteria obtained by each Technique with One-year of Historical Data usage

Fig. 5.165. Different Performance criteria obtained by each Technique with Two-years of Historical Data usage

Fig. 5.166. Different Performance criteria obtained by each Technique with Three-years of Historical Data usage

Fig. 5.167. Different Performance criteria obtained by each Technique with Four-years of Historical Data usage

Fig. 5.168. Different Performance criteria obtained by each Technique with Five-years of Historical Data usage

Fig. 6.1. Block Diagram Representation of EPLF Model developed without Calendar Features

Fig. 6.2 Instantaneous samples of obtained forecast error in MvLR Technique developed without Calendar Features

Fig. 6.3. Pie chart of Forecast error in MvLR Technique developed without Calendar Features

Fig. 6.4. Daily Forecast Error obtained in MvLR Technique developed without Calendar Features

Fig. 6.5. Daily MAPE obtained in MvLR Technique developed without Calendar Features

Fig. 6.6. Daily MAE obtained in MvLR Technique developed without Calendar Features

Fig. 6.7. Daily RMSE obtained in MvLR Technique developed without Calendar Features

Fig. 6.8 Instantaneous samples of obtained forecast error in FFNN Technique developed without Calendar Features

Fig. 6.9. Pie chart of Forecast error in FFNN Technique developed without Calendar Features

Fig. 6.10. Daily Forecast Error obtained in FFNN Technique developed without Calendar Features

Fig. 6.11. Daily MAPE obtained in FFNN Technique developed without Calendar Features

Fig. 6.12. Daily MAE obtained in FFNN Technique developed without Calendar Features

Fig. 6.13. Daily RMSE obtained in FFNN Technique developed without Calendar Features

Fig. 6.14 Instantaneous samples of obtained forecast error in CFNN Technique developed without Calendar Features

Fig. 6.15. Pie chart of Forecast error in CFNN Technique developed without Calendar Features

Fig. 6.16. Daily Forecast Error in CFNN Technique developed without Calendar Features

Fig. 6.17. Daily MAPE obtained in CFNN Technique developed without Calendar Features

Fig. 6.18. Daily MAE obtained in CFNN Technique developed without Calendar Features

Fig. 6.19. Daily RMSE obtained in CFNN Technique developed without Calendar Features

Fig. 6.20 Instantaneous samples of obtained forecast error in FFitNN Technique developed without Calendar Features

Fig. 6.21. Pie chart of Forecast error in FFitNN Technique developed without Calendar Features

Fig. 6.22. Daily Forecast Error obtained in FFitNN Technique developed without Calendar Features

Fig. 6.23. Daily MAPE obtained in FFitNN Technique developed without Calendar Features

Fig. 6.24. Daily MAE obtained in FFitNN Technique developed without Calendar Features

Fig. 6.25. Daily RMSE obtained in FFitNN Technique developed without Calendar Features

Fig. 6.26 Instantaneous samples of obtained forecast error in LRcNN Technique developed without Calendar Features

Fig. 6.27. Pie chart of Forecast error in LRcNN Technique developed without Calendar Features

Fig. 6.28. Daily Forecast Error in LRcNN Technique developed without Calendar Features

Fig. 6.29. Daily MAPE obtained in LRcNN Technique developed without Calendar Features

Fig. 6.30. Daily MAE obtained in LRcNN Technique developed without Calendar Features

Fig. 6.31. Daily RMSE obtained in LRcNN Technique developed without Calendar Features

Fig. 6.32 Instantaneous samples of obtained forecast error in Standard LSTM Technique developed without Calendar Features

Fig. 6.33. Pie chart of Forecast error in Standard LSTM Technique developed without Calendar Features

Fig. 6.34. Daily Forecast Error obtained in Standard LSTM Technique developed without Calendar Features

Fig. 6.35. Daily MAPE obtained in Standard LSTM Technique developed without Calendar Features

Fig. 6.36. Daily MAE obtained in Standard LSTM Technique developed without Calendar Features

Fig. 6.37. Daily RMSE obtained in Standard LSTM Technique developed without Calendar Features

Fig. 6.38 Instantaneous samples of obtained forecast error in S2S LSTM Technique developed without Calendar Features

Fig. 6.39. Pie chart of Forecast error in S2S LSTM Technique developed without Calendar Features

Fig. 6.40. Daily Forecast Error obtained in S2S LSTM Technique developed without Calendar Features

Fig. 6.41. Daily MAPE obtained in S2S LSTM Technique developed without Calendar Features

Fig. 6.42. Daily MAE obtained in S2S LSTM Technique developed without Calendar Features

Fig. 6.43. Daily RMSE obtained in S2S LSTM Technique developed without Calendar Features

Fig. 6.44. Type of Consumer wise forecast error obtained by each technique developed without Calendar Features

Fig. 6.45. Type of Tariff wise forecast error obtained by each technique developed without Calendar Features

Fig. 6.46. Different Performance criteria obtained by each Technique without Calendar Features

Fig. 6.47. Block Diagram Representation of EPLF Model developed without Weather Features

Fig. 6.48 Instantaneous samples of obtained forecast error in MvLR Technique developed without Weather Features

Fig. 6.49. Pie chart of Forecast error in MvLR Technique developed without Weather Features

Fig. 6.50. Daily Forecast Error obtained in MvLR Technique developed without Weather Features

Fig. 6.51. Daily MAPE obtained in MvLR Technique developed without Weather Features

Fig. 6.52. Daily MAE obtained in MvLR Technique developed without Weather Features

Fig. 6.53. Daily RMSE obtained in MvLR Technique developed without Weather Features

Fig. 6.54 Instantaneous samples of obtained forecast error in FFNN Technique developed without Weather Features

Fig. 6.55. Pie chart of Forecast error in FFNN Technique developed without Weather Features

Fig. 6.56. Daily Forecast Error obtained in FFNN Technique developed without Weather Features

Fig. 6.57. Daily MAPE obtained in FFNN Technique developed without Weather Features

Fig. 6.58. Daily MAE obtained in FFNN Technique developed without Weather Features

Fig. 6.59. Daily RMSE obtained in FFNN Technique developed without Weather Features

Fig. 6.60. Instantaneous samples of obtained forecast error in CFNN Technique developed without Weather Features

Fig. 6.61. Pie chart of Forecast error in CFNN Technique developed without Weather Features

Fig. 6.62. Daily Forecast Error in CFNN Technique developed without Weather Features

Fig. 6.63. Daily MAPE obtained in CFNN Technique developed without Weather Features

Fig. 6.64. Daily MAE obtained in CFNN Technique developed without Weather Features

Fig. 6.65. Daily RMSE obtained in CFNN Technique developed without Weather Features

Fig. 6.66. Instantaneous samples of obtained forecast error in FFitNN Technique developed without Weather Features

Fig. 6.67. Pie chart of Forecast error in FFitNN Technique developed without Weather Features

Fig. 6.68. Daily Forecast Error obtained in FFitNN Technique developed without Weather Features

Fig. 6.69. Daily MAPE obtained in FFitNN Technique developed without Weather Features

Fig. 6.70. Daily MAE obtained in FFitNN Technique developed without Weather Features

Fig. 6.71. Daily RMSE obtained in FFitNN Technique developed without Weather Features

Fig. 6.72 Instantaneous samples of obtained forecast error in LRcNN Technique developed without Weather Features

Fig. 6.73. Pie chart of Forecast error in LRcNN Technique developed without Weather Features

Fig. 6.74. Daily Forecast Error obtained in LRcNN Technique developed without Weather Features

Fig. 6.75. Daily MAPE obtained in LRcNN Technique developed without Weather Features

Fig. 6.76. Daily MAE obtained in LRcNN Technique developed without Weather Features

Fig. 6.77. Daily RMSE obtained in LRcNN Technique developed without Weather Features

Fig. 6.78 Instantaneous samples of obtained forecast error in Standard LSTM Technique developed without Weather Features

Fig. 6.79. Pie chart of Forecast error in Standard LSTM Technique developed without Weather Features

Fig. 6.80. Daily Forecast Error obtained in Standard LSTM Technique developed without Weather Features

Fig. 6.81. Daily MAPE obtained in Standard LSTM Technique developed without Weather Features

Fig. 6.82. Daily MAE obtained in Standard LSTM Technique developed without Weather Features

Fig. 6.83. Daily RMSE obtained in Standard LSTM Technique developed without Weather Features

Fig. 6.84 Instantaneous samples of obtained forecast error in S2S LSTM Technique developed without Weather Features

Fig. 6.85. Pie chart of Forecast error in S2S LSTM Technique developed without Weather Features

Fig. 6.86. Daily Forecast Error obtained in S2S LSTM Technique developed without Weather Features

Fig. 6.87. Daily MAPE obtained in S2S LSTM Technique developed without Weather Features

Fig. 6.88. Daily MAE obtained in S2S LSTM Technique developed without Weather Features

Fig. 6.89. Daily RMSE obtained in S2S LSTM Technique developed without Weather Features

Fig. 6.90. Season wise forecast error obtained by each technique without Weather Features

Fig. 6.91. Month wise forecast error obtained by each technique without Weather Features

Fig. 6.92. Day of the Week wise forecast error obtained by each technique without Weather Features

Fig. 6.93. Weekend wise forecast error obtained by each technique without Weather Features

Fig. 6.94. Special day wise forecast error obtained by each technique without Weather Features

Fig. 6.95. IndustryOFF wise forecast error obtained by each technique without Weather Features

Fig. 6.96. Type of Consumer wise forecast error obtained by each technique without Weather Features

Fig. 6.97. Type of Tariff wise forecast error obtained by each technique without Weather Features

Fig. 6.98. Different Performance criteria obtained by each Technique developed without Weather Features

Fig. 6.99. Block Diagram Representation of Architecture of ELPF Model developed without Smart grid Features

Fig. 6.100. Instantaneous samples of obtained forecast error in MvLR Technique developed without Smart grid Features

Fig. 6.101. Pie chart of Forecast error in MvLR Technique developed without Smart grid Features

Fig. 6.102. Daily Forecast Error obtained in MvLR Technique developed without Smart grid Features

Fig. 6.103. Daily MAPE obtained in MvLR Technique developed without Smart grid Features

Fig. 6.104. Daily MAE obtained in MvLR Technique developed without Smart grid Features

Fig. 6.105. Daily RMSE obtained in MvLR Technique developed without Smart grid Features

Fig. 6.106. Instantaneous samples of obtained forecast error in FFNN Technique developed without Smart grid Features

Fig. 6.107. Pie chart of Forecast error in FFNN Technique developed without Smart grid Features

Fig. 6.108. Daily Forecast Error obtained in FFNN Technique developed without Smart grid Features

Fig. 6.109. Daily MAPE obtained in FFNN Technique developed without Smart grid Features

Fig. 6.110. Daily MAE obtained in FFNN Technique developed without Smart grid Features

Fig. 6.111. Daily RMSE obtained in FFNN Technique developed without Smart grid Features

Fig. 6.112 Instantaneous samples of obtained forecast error in CFNN Technique developed without Smart grid Features

Fig. 6.113. Pie chart of Forecast error in CFNN Technique developed without Smart grid Features

Fig. 6.114. Daily Forecast Error obtained in CFNN Technique developed without Smart grid Features

Fig. 6.115. Daily MAPE obtained in CFNN Technique developed without Smart grid Features

Fig. 6.116. Daily MAE obtained in CFNN Technique developed without Smart grid Features

Fig. 6.117. Daily RMSE obtained in CFNN Technique developed without Smart grid Features

Fig. 6.118. Instantaneous samples of obtained forecast error in FFitNN Technique developed without Smart grid Features

Fig. 6.119. Pie chart of Forecast error in FFitNN Technique developed without Smart grid Features

Fig. 6.120. Daily Forecast Error obtained in FFitNN Technique developed without Smart grid Features

Fig. 6.121. Daily MAPE obtained in FFitNN Technique developed without Smart grid Features

Fig. 6.122. Daily MAE obtained in FFitNN Technique developed without Smart grid Features

Fig. 6.123. Daily RMSE obtained in FFitNN Technique developed without Smart grid Features

Fig. 6.124. Instantaneous samples of obtained forecast error in LRCNN Technique developed without Smart grid Features

Fig. 6.125. Pie chart of Forecast error in LRcNN Technique developed without Smart grid Features

Fig. 6.126. Daily Forecast Error obtained in LRcNN Technique developed without Smart grid Features

Fig. 6.127. Daily MAPE obtained in LRcNN Technique developed without Smart grid Features

Fig. 6.128. Daily MAE obtained in LRcNN Technique developed without Smart grid Features

Fig. 6.129. Daily RMSE obtained in LRcNN Technique developed without Smart grid Features

Fig. 6.130. Instantaneous samples of obtained forecast error by Standard LSTM Technique developed without Smart grid Features

Fig. 6.131. Pie chart of Forecast error by Standard LSTM Technique developed without Smart grid Features

Fig. 6.132. Daily Forecast Error obtained in Standard LSTM Technique developed without Smart grid Features

Fig. 6.133. Daily MAPE obtained in Standard LSTM Technique developed without Smart grid Features

Fig. 6.134. Daily MAE obtained in Standard LSTM Technique developed without Smart grid Features

Fig. 6.135. Daily RMSE obtained in Standard LSTM Technique developed without Smart grid Features

Fig. 6.136. Instantaneous samples of obtained forecast error in S2S LSTM Technique developed without Smart grid Features

Fig. 6.137. Pie chart of Forecast error in S2S LSTM Technique developed without Smart grid Features

Fig. 6.138. Daily Forecast Error obtained in S2S LSTM Technique developed without Smart grid Features

Fig. 6.139. Daily MAPE obtained in S2S LSTM Technique developed without Smart grid Features

Fig. 6.140. Daily MAE obtained in S2S LSTM Technique developed without Smart grid Features

Fig. 6.141. Daily RMSE obtained in S2S LSTM Technique developed without Smart grid Features

Fig. 6.142. Season wise forecast error obtained by each technique without Smart grid Features

Fig. 6.143. Month wise forecast error obtained by each technique without Weather Features

Fig. 6.144. Day of the Week wise forecast error obtained by each technique without Smart grid Features

Fig. 6.145. Weekend wise forecast error obtained by each technique without Smart grid Features

Fig. 6.146. Special day wise forecast error obtained by each technique without Smart grid Features

Fig. 6.147. IndustryOFF wise forecast error obtained by each technique without Smart grid Features

Fig. 6.148. Different Performance criteria obtained by each Technique without Smart grid Features

Fig. 6.149. Block diagram representation of Architecture for EPLF Model Development with Temperature Forecast Errors

Fig. 6.150. Different Performance criteria obtained by each case in MvLR Technique with Temperature forecast errors

Fig. 6.151. Different Performance criteria obtained by each case in FFNN Technique with Temperature forecast errors

Fig. 6.152. Different Performance criteria obtained by each case in CFNN Technique with Temperature forecast errors

Fig. 6.153. Different Performance criteria obtained by each case in FFitNN Technique with Temperature forecast errors

Fig. 6.154. Different Performance criteria obtained by each case in LRcNN Technique with Temperature forecast errors

Fig. 6.155. Different Performance criteria obtained by each case in standard LSTM Technique with Temperature forecast errors

Fig. 6.156. Different Performance criteria obtained by each case in sequence-to-sequence regression LSTM Technique with Temperature forecast errors

Fig. 6.157. Different Performance criteria obtained in different Technique with zero Temperature forecast errors

Fig. 6.158. Different Performance criteria obtained in different Technique with 5% Temperature forecast errors

Fig. 6.159. Different Performance criteria obtained in different Technique with 10% Temperature forecast errors

Fig. 6.160. Block diagram representation of Architecture for EPLF Model Development with Relative Humidity Forecast Errors

Fig. 6.161. Different Performance criteria obtained by each case in MvLR Technique with different values of relative humidity forecast errors

Fig. 6.162. Different Performance criteria obtained by each case in FFNN Technique with different values of relative humidity forecast errors

Fig. 6.163. Different Performance criteria obtained by each case in CFNN Technique with different values of relative humidity forecast errors

Fig. 6.164. Different Performance criteria obtained by each case in FFitNN Technique with different values of relative humidity forecast errors

Fig. 6.165. Different Performance criteria obtained by each case in LRcNN Technique with different values of relative humidity forecast errors

Fig. 6.166. Different Performance criteria obtained by each case in standard LSTM Technique with different values of relative humidity forecast errors

Fig. 6.167. Different Performance criteria obtained by each case in sequence-to-sequence regression LSTM Technique with different values of relative humidity forecast errors

Fig. 6.168. Different Performance criteria obtained in different Technique with zero Relative Humidity forecast errors

Fig. 6.169. Different Performance criteria obtained in different Technique with 5% Relative Humidity forecast errors

Fig. 6.170. Different Performance criteria obtained in different Technique with 10% Relative Humidity forecast error

Fig. 6.171. Block diagram representation of Architecture for EPLF Model Development with Wind Speed Forecast Errors

Fig. 6.172. Different Performance criteria obtained by each case in MvLR Technique with different values of wind speed forecast errors

Fig. 6.173. Different Performance criteria obtained by each case in FFNN Technique with different values of wind speed forecast errors

Fig. 6.174. Different Performance criteria obtained by each case in CFNN Technique with different values of wind speed forecast errors

Fig. 6.175. Different Performance criteria obtained by each case in FFitNN Technique with different values of wind speed forecast errors

Fig. 6.176. Different Performance criteria obtained by each case in LRcNN Technique with different values of wind speed forecast errors

Fig. 6.177. Different Performance criteria obtained by each case in standard LSTM Technique with different values of wind speed forecast errors

Fig. 6.178. Different Performance criteria obtained by each case in sequence-to-sequence regression LSTM Technique with different values of wind speed forecast errors

Fig. 6.179. Different Performance criteria obtained in different Technique with zero Wind Speed Forecast error

Fig. 6.180. Different Performance criteria obtained in different Technique with 5% Wind Speed forecast errors

Fig. 6.181. Different Performance criteria obtained in different Technique with 10% Wind Speed Forecast error

Fig. 6.182. Block diagram representation of Architecture for EPLF Model Development with Wind Speed Forecast Errors

Fig. 6.183. Different Performance criteria obtained by each case in MvLR Technique with different values of weather forecast errors

Fig. 6.184. Different Performance criteria obtained by each case in FFNN Technique with different values of weather forecast errors

Fig. 6.185. Different Performance criteria obtained by each case in CFNN Technique with different values of Weather forecast errors

Fig. 6.186. Different Performance criteria obtained by each case in FFitNN Technique with different values of weather forecast errors

Fig. 6.187. Different Performance criteria obtained by each case in LRcNN Technique with different values of weather forecast errors

Fig. 6.188. Different Performance criteria obtained by each case in Standard LSTM Technique with different values of weather forecast errors

Fig. 6.189. Different Performance criteria obtained by each case in sequence-to-sequence regression LSTM Technique with different values of weather forecast errors

Fig. 6.190. Different Performance criteria obtained in different Technique with zero weather forecast errors

Fig. 6.191. Different Performance criteria obtained in different Technique with 5% weather forecast errors

Fig. 6.192. Different Performance criteria obtained in different Technique developed with 10% weather forecast errors

LIST OF TABLES

Table. 1.1. Need of forecasts in EDUs

Table. 2.1. Holidays (Special days) Selected

Table. 3.1. Input Features (Variables) chosen for EPLF Model Development

Table. 3.2. Interpretation of Correlation Coefficient

Table. 3.3. Correlation coefficient obtained by Pearson correlation Method

Table. 3.4. Ranking obtained by RReliefF method for“K=50”

Table. 4.1. Size of Data-set

Table. 4. 2. Selection of different ANN Parameters

Table. 4.3. Selection of LSTM Network Parameters

Table. 4.4. Selection of Training Parameters

Table. 4.5. Obtained value of β coefficients in MvLR Technique

Table. 4.6. Performance of different ANNs of Model

Table. 4.7. Season wise Forecast error obtained by each technique

Table. 4.8. Month wise Forecast error obtained by each technique

Table. 4.9. Performance Criteria obtained by each technique

Table. 5.1. Season wise Forecast error obtained by each technique developed in Similar Day Method

Table 5.2. Month wise Forecast error obtained by each technique in Similar Day Method

Table. 5.3. Performance Criteria obtained in each technique developed with Similar Day Method

Table. 5.4. Season wise Forecast error obtained by each technique developed in SM Method

Table 5.5. Month wise Forecast error obtained by each technique developed in SM Method

Table. 5.6. Performance Criteria obtained by each technique developed in Similar Month Method

Table. 5.7. Season wise Forecast error obtained by each technique in Special Day Method

Table. 5.8. Month wise Forecast error obtained by each technique in Special Day Method

Table. 5.9. Performance Criteria obtained by each technique in Special Day Method

Table. 5.10. Size of Data-set

Table. 5.11. Performance Criteria obtained in MvLR Technique with Greater number of years Method

Table. 5.12. Performance Criteria obtained in FFNN Technique with Greater number of years Method

Table. 5.13. Performance Criteria obtained in CFNN Technique with Greater number of years Method

Table. 5.14. Performance Criteria obtained in FFitNN Technique with Greater number of years Method

Table. 5.15. Performance Criteria obtained in LRcNN Technique with Greater number of years Method

Table. 5.16. Performance Criteria obtained in standard LSTM Technique with Greater number of years Method

Table. 5.17. Performance Criteria obtained in Sequence-to-Sequence Regression LSTM Technique With Greater number of years Method

Table. 5.18. Performance Criteria obtained by each Technique with One-year of Historical Data usage

Table. 5.19. Performance Criteria obtained by each Technique with Two-years of Historical Data usage

Table. 5.20. Performance Criteria obtained by each Technique with Three-years of Historical Data usage

Table. 5.21. Performance Criteria obtained by each Technique with Four-years of Historical Data usage

Table. 5.22. Performance Criteria obtained by each Technique with Five-years of Historical Data usage

Table. 5.23. Comparison of Lowest Error Obtained in Different Methods discussed in Chapter 5

Table. 5.24. Comparison of Highest Error Obtained in Different Methods discussed in Chapter 5

Table. 6.1. Performance Criteria obtained by each technique developed without Calendar Features

Table. 6.2. Season wise Forecast error obtained by each technique developed without Weather Features

Table. 6.3. Month wise Forecast error obtained by each technique developed without Weather Features

Table 6.4. Performance Criteria obtained by each technique developed without Weather Features

Table. 6.5. Season wise Forecast error obtained by each technique developed without Smart grid Features

Table. 6.6. Month wise Forecast error obtained by each technique developed without Smart grid Features

Table 6.7. Performance Criteria obtained by each technique developed without Smart grid Features

Table. 6.8. Different Cases Chosen Temperature forecast error

Table 6.9. Performance Criteria obtained by each case in MvLR Technique developed with Temperature forecast errors

Table 6.10. Performance Criteria obtained by each case in FFNN Technique developed with Temperature forecast errors

Table 6.11. Performance Criteria obtained by each case in CFNN Technique developed with Temperature forecast errors

Table. 6.12. Performance Criteria obtained by each case in FFitNN Technique developed with Temperature forecast errors

Table. 6.13. Performance Criteria obtained by each case in LRcNN Technique developed with Temperature forecast errors

Table 6.14. Performance Criteria obtained by each case in standard LSTM Technique developed with Temperature forecast errors

Table. 6.15. Performance Criteria obtained by each case in sequence-to-sequence regression LSTM Technique developed with Temperature forecast errors

Table. 6.16. Performance Criteria obtained by each technique developed with zero Temperature Forecast Error

Table 6.17. Performance Criteria obtained by each technique developed with 5% Temperature Forecast Error

Table 6.18. Performance Criteria obtained by each technique developed with 10% Temperature Forecast Error

Table. 6.19. Different Cases Chosen for Relative humidity forecast error

Table. 6.20. Performance Criteria obtained by each case in MvLR Technique developed with different values of relative humidity forecast errors

Table. 6.21. Performance Criteria obtained by each case in FFNN Technique developed with different values of relative humidity forecast errors

Table. 6.22. Performance Criteria obtained by each case in CFNN Technique developed with different values of relative humidity forecast errors

Table 6.23. Performance Criteria obtained by each case in FFitNN Technique developed with different values of relative humidity forecast errors

Table 6.24. Performance Criteria obtained by each case in LRcNN Technique developed with different values of relative humidity forecast errors

Table 6.25. Performance Criteria obtained by each case in standard LSTM Technique developed with different values of relative humidity forecast errors

Table. 6.26. Performance Criteria obtained by each case in sequence-to-sequence regression LSTM Technique developed with different values of relative humidity forecast errors

Table 6.27. Performance Criteria obtained by each technique developed with zero Relative Humidity forecast error

Table 6.28. Performance Criteria obtained by each technique developed with 5% Relative Humidity forecast error

Table 6.29. Performance Criteria obtained by each technique developed with 10% Relative Humidity forecast error

Table 6.30. Different Cases Chosen for Wind speed forecast error

Table. 6.31. Performance Criteria obtained by each case in MvLR Technique developed with different values of wind speed forecast errors

Table 6.32. Performance Criteria obtained by each case in FFNN Technique developed with different values of wind speed forecast errors

Table 6.33. Performance Criteria obtained by each case in CFNN Technique developed with different values of wind speed forecast errors

Table. 6.34. Performance Criteria obtained by each case in FFitNN Technique developed with different values of wind speed forecast errors

Table. 6.35. Performance Criteria obtained by each case in LRcNN Technique developed with different values of wind speed forecast errors

Table. 6.36. Performance Criteria obtained by each case in standard LSTM Technique developed with different values of wind speed forecast errors

Table. 6.37. Performance Criteria obtained by each case in sequence-to-sequence regression LSTM Technique developed with different values of wind speed forecast errors

Table 6.38. Performance Criteria obtained by each technique developed with zero Wind Speed Forecast error

Table. 6.39. Performance Criteria obtained by each technique developed with 5% Wind Speed Forecast error

Table 6.40. Performance Criteria obtained by each technique developed with 10% Wind Speed Forecast error

Table 6.41. Different Cases Chosen for Weather forecast error

Table. 6.42. Performance Criteria obtained by each case in MvLR Technique developed with different values of weather forecast errors

Table. 6.43. Performance Criteria obtained by each case in FFNN Technique developed with different values of weather forecast errors

Table. 6.44. Performance Criteria obtained by each case in CFNN Technique developed with different values of weather forecast errors

Table. 6.45. Performance Criteria obtained by each case in FFitNN Technique developed with different values of wind speed forecast errors

Table. 6.46. Performance Criteria obtained by each case in LRcNN Technique developed with different values of weather forecast errors

Table. 6.47. Performance Criteria obtained by each case in standard LSTM Technique developed with different values of weather forecast errors

Table. 6.48. Performance Criteria obtained by each case in Sequence-to-Sequence Regression LSTM Technique developed with different values of weather forecast errors

Table 6.49. Performance Criteria obtained by each technique developed with zero weather forecast error

Table. 6.50. Performance Criteria obtained by each technique developed with 5% weather forecast error

Table. 6.51. Performance Criteria obtained by each technique developed with 10% weather forecast error

Table. 6.52. Comparison of Lowest Error Obtained in Different Models discussed in Chapter 6

Table. 6.53. Comparison of Highest Error Obtained in Different Models discussed in Chapter 6

LIST OF ABBREVIATIONS

The symbols used in the thesis are listed below. Other symbols, not indicated in the list, have been defined locally.

EDU- Electric Power Distribution utility

EPLF- Electric Power Load Forecasting

DSM- Demand Side Management

CV1- Season

CV2- Month

CV3- Day of the Week

CV4- Week end factor

CV5- Holiday(Special day) factor

CV6-IndustryOFF factor

Ta - Air Temperature

Rh - Relative Humidity

Ws- Wind Speed

(D-1) P_L - Previous Day Electric Power Load

cnT -Type of Consumer

tfT -Type of Tariff

MvLR- Multi-variate Linear Regression

FFNN- Feed-forward Neural Network

CFNN- Cascade Forward Neural Network

FFitNN- Function Fitting Neural Network

LRcNN-Layer Recurrent Neural Network