

**RESIDENTIAL SAUDI LOAD FORECASTING  
USING ANALYTICAL MODEL AND  
ARTIFICIAL NEURAL NETWORKS**

BY

Ahmad Abdulaziz Al-Harbi

A Thesis Presented to the  
DEANSHIP OF GRADUATE STUDIES

**KING FAHD UNIVERSITY OF PETROLEUM & MINERALS**

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the  
Requirements for the Degree of

**MASTER OF SCIENCE**

In

**ELECTRICAL ENGINEERING**

April, 2012

**KING FAHD UNIVERSITY OF PETROLEUM & MINERALS  
DHAHRAN, SAUDI ARABIA**

**DEANSHIP OF GRADUATE STUDIES**

This thesis, written by **AHMAD ABDULAZIZ AL-HARBI** under the direction of his thesis advisor and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING**.

**Thesis Committee**



Dr. Chokri Belhaj Ahmed (Advisor)




Dr. Ibrahim M. El-Amin (Member)



Dr. Mahmoud Kassas (Member)



Dr. Ali A. Al-Shaikhi  
Department Chairman



Dr. Salam A. Zummo  
Dean of Graduates Studies



Date 24/4/20

## إهداء

- إلى والديّ العزيزين .. أسأل الله أن يحفظكما .. و يطيل أعماركما  
على طاعته ..

- إلى زوجتي الغالية .. التي كانت عوناً لي بعد الله .. لإنجاز هذا  
العمل ..

- إلى أبنائي .. أريام و عمار .. أسأل الله أن يصلحكما .. و ينبتكما نباتاً  
حسناً ..

- إلى من أحب .. أخواني و أخواتي ..

- إلى كل من ساعدني .. برأي .. أو نصيحة .. أو دعوة صادقة ..

# ACKNOWLEDGMENT

*In the name of Allah, Most Gracious, Most Merciful*

First of all, I thank and pray to Allah for his guidance and protection throughout my life, including the years of this study. Peace and blessings of Allah be on his last Messenger, Muhammad.

I would like to thank my parents for their encouragements and support, my wife who was very patient in supporting me to finish this work, and all of my brothers, sisters and friends for their support.

I am very thankful to Royal Commission of Yanbu for giving me this opportunity to continue my higher education.

Acknowledgment is due to King Fahd University of Petroleum & Minerals for supporting this research.

I am deeply indebted to my thesis advisor Dr. Chokri Belhaj Ahmad for his constant guidance, support, encouragement throughout the course of this research. He made my pursuit of higher education a truly enjoyable and unforgettable experience. At the later stages he helped me a lot in writing my thesis.

I also wish to thank the other members of my thesis committee Dr. Ibrahim El-Amin and Dr. Mahmoud Kassas for their cooperation, encouragement and help.

Thanks are also to the Saudi Electricity Company-Eastern Region Branch represented by Mr. Abdullah Al-Najim who provided me with the helpful information and data needed for this work.

Special thanks are to Mr. Ibrahim Al-Subhi, Eng. Salman Al-Zahrani and Eng. Faisal Bahussain from Marafiq Company in Yanbu who provided me with the relevant data for Yanbu Industrial City.

I want also to thank Eng. Ehab Al-Judaibi who provided me with the relevant data for Jeddah and entire western region.

Also, thanks to Dr. Radwan Abdel-Aal from KFUPM, Computer Engineering department for providing me with the data for Seattle, USA

Lastly but not the least, thanks to everyone helped me by giving any idea, suggestion, support, encouragement and supplication.

# TABLE OF CONTENTS

Acknowledgments .....	iv	
List Of Tables .....	x	
List Of Figures .....	xi	
Thesis Abstract (English) .....	xvi	
Thesis Abstract (Arabic).....	xvii	
<b>CHAPTER 1: INTRODUCTION</b>		
1.1 Overview .....	1	
1.2 Classification of Power System Load Forecasting .....	2	
1.2.1 Short-Term Load Forecasting (STLF) .....	2	
1.2.2 Mid-Term Load Forecasting (MTLF) .....	4	
1.2.3 Long-Term Load Forecasting (LTLF) .....	4	
1.3 Prerequisites of Good STLF System.....	5	
1.4 Saudi Load Characteristics .....	5	
1.5 Scope and Objective of the Work .....	9	
1.6 Structure of the Work.....	11	
<b>CHAPTER 2: LITERATURE REVIEW</b> .....		12
2.1 Fuzzy Logic .....	13	
2.2 Expert Systems.....	15	
2.3 Particle Swarm Optimization (PSO).....	16	
2.4 Wavelets.....	17	
2.5 Regression Methods.....	18	
2.6 Similar Days Approach.....	20	
2.7 Time Series .....	21	
2.8 Support Vector Machine (SVM).....	22	
<b>CHAPTER 3: DATA ANALYSIS AND MODES CLASSIFICATION</b>		
3.1 Overview .....	24	
3.2 Data Filtering .....	25	
3.3 Data Sources .....	25	

3.4 Data Analysis .....	27
3.4.1 Overview .....	27
3.4.2 Load Variation .....	27
3.4.2.1 Daily Behavior.....	27
3.4.2.2 Seasonal Behavior.....	29
3.4.2.3 Annual Behavior .....	30
3.5 Special Days Analysis.....	31
3.6 Modes Classification.....	31
3.6.1 SEC Data .....	31
3.6.1.1 Ramadan Mode.....	36
3.6.1.2 Eid Feter Day Mode.....	37
3.6.1.3 After Eid Feter day Mode.....	38
3.6.1.4 Eid Hajj Day Mode .....	39
3.6.1.5 After Eid Hajj Day Mode .....	40
3.6.1.6 Cold Normal Days Mode .....	40
3.6.1.7 Cold Thursdays Mode.....	41
3.6.1.8 Cold Fridays Mode.....	42
3.6.1.9 Hot Normal Days Mode .....	42
3.6.1.10 Hot Thursdays Mode .....	43
3.6.1.11 Hot Fridays Mode .....	43
3.6.2 Marafiq Data .....	45
3.6.3 USA Data.....	49
3.7 Summary and Conclusions of the Chapter.....	52

## **CHAPTER 4: ANALYSIS OF THE APPROACHES USED**

4.1 Neural Network Model (NN).....	53
4.1.1 Overview .....	53
4.1.2 NNs Applications .....	54
4.1.3 Neuron Model .....	55
4.1.4 Network Architectures .....	56
4.1.4.1 A Layer of Neurons .....	56
4.1.4.2 Multiple Layers of Neurons .....	58

4.1.5 Proposed NN model .....	59
4.1.5.1 Input Vector Configuration .....	60
4.1.5.2 Data Preprocessing.....	63
4.2 Hybrid Analytical Model .....	63
4.2.1 Fourier Transform Concept.....	64
4.2.2 Modes Analysis .....	65
4.2.2.1 Hot Fridays Mode .....	69
4.2.2.2 Ramadan Mode.....	74
4.2.2.3 Eid Feter Day Mode.....	74
4.2.2.4 After Eid Feter Day Mode.....	75
4.2.2.5 Eid Hajj Day Mode .....	75
4.2.2.6 After Eid Hajj Day Mode .....	76
4.2.2.7 Hot Week Days Mode .....	76
4.2.2.8 Hot Thursdays Mode .....	77
4.2.2.9 Summer Vacation Week Days Mode .....	77
4.2.2.10 Summer Vacation Thursays Mode.....	78
4.2.2.11 Summer Vacation Fridays Mode.....	78
4.2.2.12 Mid-Year Vacation Mode .....	79
4.2.2.13 Cold Week Days Mode .....	79
4.2.2.14 Cold Thursdays Mode .....	80
4.2.2.15 Cold Fridays Mode .....	80
4.2.3 Carrier Analysis.....	81
4.3 Summary and Conclusions of the Chapter.....	83
<b>CHAPTER 5: RESULTS AND ANALYSIS .....</b>	<b>84</b>
5.1 SEC Data.....	85
5.1.1 Next Hour Load Forscasting .....	86
5.1.1.1 ANN Model .....	86
5.1.1.2 Hybrid Analytical Model.....	88
5.1.2 Next Day Load Forecasting.....	91
5.1.2.1 ANN Model .....	91
5.1.2.2 Hybrid Analytical Model.....	94



5.1.2.3 Iterative Forecasting Model .....	97
5.2 Marafiq Data .....	101
5.2.1 Next Hour Load Forecasting .....	101
5.2.1.1 ANN Model .....	101
5.2.1.2 Hybrid Analytical Model.....	104
5.2.2 Next Day Load Forecasting.....	107
5.2.2.1 ANN Model .....	107
5.2.2.2 Hybrid Analytical Model.....	109
5.2.2.3 Iterative Forecasting Model .....	112
5.3 Summary and Conclusions of the Chapter.....	115
 <b>CHAPTER 6: MODELS COMPARISON WITH OTHER PUBLISHED WORK</b>	
6.1 Introduction.....	116
6.2 Abductory Inductive Mechanism Networks .....	117
6.3 Next Hour Load Forecasting.....	120
6.3.1 Abductive Network Model.....	120
6.3.2 ANN Model.....	121
6.3.3 Hybrid Analytical Model .....	122
6.4 Next Day Load Forecasting .....	125
6.4.1 Abductive Network Model.....	125
6.4.2 ANN Model.....	126
6.4.3 Hybrid Analytical Model .....	126
6.4.4 Iterative Forecasting Model.....	132
6.5 Summary and Conclusions of the Chapter.....	137
 <b>CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS.....</b>	
<b>APPINDIX A.....</b>	<b>141</b>
<b>APPENDIX B.....</b>	<b>142</b>
<b>APPINDIX C.....</b>	<b>144</b>
<b>APPINDIX D.....</b>	<b>146</b>
<b>APPINDIX E.....</b>	<b>148</b>
<b>REFERENCES .....</b>	<b>153</b>
<b>VITAE.....</b>	<b>159</b>

## LIST OF TABLES

Table	page
1.1: Different types of forecasting and their applications.....	5
3.1: Sample day from SEC data for 1 <sup>st</sup> January, 2002 .....	26
4.1: Summary of parameters selected in the proposed models .....	60
4.2: Input configuration for next hour load forecasting .....	60
4.3: Input parameters values to forecast hour 9 of 5 August, 2011 .....	61
4.4: Input configuration for next day load forecasting .....	62
4.5: Amplitudes and phase angles values for Hot Fridays mode.....	72
5.1: The selected dates to represent seasons for all models, SEC data.....	85
5.2: The selected dates to represent seasons for all models, Marafiq data .....	101
5.3: Summary of MAPE results of next hour models for SEC and Marafiq data.....	107
5.4: Summary of MAPE results of next day models for SEC and Marafiq data .....	115
6.1: Inputs parameters configuration for next hour load forecasting.....	120
6.2: Summary of the abductive network models for the 24 next-hour load forecasters .....	121
6.3: Performance of next-hour load forecasting models over the evaluation year ....	124
6.4: Inputs parameters configuration for next day load forecasting .....	126
6.5: Abductive network models for the 24 next-day hourly load forecasters .....	127
6.6: MAPE comparison between the four models for each day for next day load forecasting .....	133
6.7: Amplitudes and phase angles for the actual Labor Day and the five years average ac mode day .....	136

## LIST OF FIGURES

Figure	page
1.1: The annual peak load for a residential area in Al-khubar, Agrabiah distinct .....	6
1.2: Power and temperature profiles for Agrabia substation, 2002 .....	7
1.3: Power and temperature profiles for USA, Seattle, 1989.....	8
3.1: Active Power, temperature and humidity profiles for 1 <sup>st</sup> February, 2000, SEC, Agrabia substation .....	28
3.2: Active Power, Temperature and Humidity profiles for a sample day from each season, 2000, SEC, Agrabia substation .....	29
3.3: (a) Active Power, (b) Temperature and (c) Humidity profiles for year 2000, SEC, Agrabia substation .....	30
3.4: (a) Hourly load profile for years 1998 to 2006, SEC data (b) Annual peak load for years 1998 to 2006, SEC data .....	32
3.5: Sample 11 days for different modes in 1999 .....	33
3.6: Typical cold region week, 1998, 1999 and 2000 .....	34
3.7: Typical winter and summer days, 1999 .....	35
3.8: Typical Ramadan days, 1999 .....	36
3.9: Typical Ramadan day, 1998, 1999 and 2000.....	37
3.10: Eid Feter day, 1998, 1999 and 2000 .....	38
3.11: Eid Hajj day, 1999 and 2000 .....	39
3.12: Eid Hajj day and its previous and next modes, 1999.....	40
3.13: Typical Thursdays, cold region, 1998, 1999 and 2000.....	41
3.14: Typical Fridays, cold region, 1998, 1999 and 2000 .....	42
3.15: Typical hot region week, 1998, 1999 and 2000.....	43
3.16: Typical Thursdays, hot region, 1998, 1999 and 2000 .....	44
3.17: Typical Fridays, hot region, 1998, 1999 and 2000 .....	44
3.18: (a) Power and temperature profiles for Marafiq data, 2009 (b) Daily peak demands and temperatures for Marafiq data, 2009.....	46
3.19: Power and temperature profiles, Yanbu industrial city, Ramadan, 2009 .....	47
3.20: Power and temperature profiles, Yanbu industrial city, 14/2-13/3/2009.....	48
3.21: Load profile for sample week from each season, Seattle, USA, 1989 .....	50

3.22: Power profile for some special days in Seattle, USA, 1989 .....	51
4.1: Concept of NN .....	54
4.2: (a) Neuron with a single scalar input and no bias (b) Neuron with a scalar bias .....	55
4.3: One-layer network .....	56
4.4: One-layer network with R input elements and S neurons .....	57
4.5: Multiple Layers of Neurons .....	58
4.6: Steps used in modes analysis modeling .....	67
4.7: Power profile for years 2009 to 10 December 2011 for Marafiq data.....	68
4.8: Power profile with ac and dc components, Marafiq, 2009 .....	68
4.9: (a) Hot Fridays for years 2009 and 2010, Marafiq (b) Hot Fridays similarity for years 2009 and 2010, Marafiq.....	70
4.10: Average day for hot Fridays mode .....	71
4.11: Amplitudes and phase angles of the average mode day .....	72
4.12: Final average daily modeled load curve for hot Fridays mode.....	73
4.13: (a) Ramadan days for years 2009 and 2010 (b) Final average daily modeled load curve for Ramadan mode .....	74
4.14: (a) Eid Feter days for years 2009 and 2010 (b) Final average daily modeled load curve for Eid Feter mode .....	74
4.15: (a) After Eid Feter days for years 2009 and 2010 (b) Final average daily modeled load curve for After Eid Feter days mode.....	75
4.16: (a) Eid Hajj days for years 2009 and 2010 (b) Final average daily modeled load curve for Eid Hajj mode.....	75
4.17: (a) After Eid Hajj days for years 2009 and 2010 (b) Final average daily modeled load curve for After Eid Hajj mode .....	76
4.18: (a) Hot week days for years 2009 and 2010 (b) Final average daily modeled load curve for hot week days mode .....	76
4.19: (a) Hot Thursdays for years 2009 and 2010 (b) Final average daily modeled load curve for hot Thursdays mode .....	77
4.20: (a) Summer vacation week days for years 2009 and 2010 (b) Final average daily modeled load curve for summer vacation week days mode ...	77
4.21: (a) Summer vacation Thursdays for years 2009 and 2010 (b) Final average daily modeled load curve for summer vacation Thursdays mode ...	78
4.22: (a) Summer vacation Fridays for years 2009 and 2010 (b) Final average daily modeled load curve for summer vacation Fridays mode.....	78
4.23: (a) Mid-year vacation days for years 2009 and 2010 (b) Final average daily modeled load curve for mid-year vacation mode .....	79

4.24: (a) Cold week days for years 2009 and 2010	
(b) Final average daily modeled load curve for cold week days mode .....	79
4.25: (a) Cold Thursdays for years 2009 and 2010	
(b) Final average daily modeled load curve for cold Thursdays mode.....	80
4.26: (a) Cold Fridays for years 2009 and 2010	
(b) Final average daily modeled load curve for Cold Fridays mode .....	80
4.27: Input configuration for next day average power forecasting .....	82
5.1: a) Actual and forecasted load for cold week period, SEC, 2005	
b) Absolute error and MAPE, next hour, NN .....	86
5.2: a) Actual and forecasted load for hot week period, SEC, 2005	
b) Absolute error and MAPE, next hour, NN .....	87
5.3: a) Actual and forecasted load for Ramadan season, SEC, 2005	
b) Absolute error and MAPE, next hour, NN .....	87
5.4: a) Actual and forecasted load for summer vacation season, SEC, 2005	
b) Absolute error and MAPE, next hour, NN .....	88
5.5: a) Actual and forecasted load for cold week period, SEC, 2005	
b) Absolute error and MAPE, next hour, analytical model .....	89
5.6: a) Actual and forecasted load for hot week period, SEC, 2005	
b) Absolute error and MAPE, next hour, analytical model .....	89
5.7: a) Actual and forecasted load for Ramadan season, SEC, 2005	
b) Absolute error and MAPE, next hour, analytical model .....	90
5.8: a) Actual and forecasted load for summer vacation season, SEC, 2005	
b) Absolute error and MAPE, next hour, analytical model .....	90
5.9: a) Actual and forecasted load for cold week period, SEC, 2005	
b) Absolute error and MAPE, next day, NN.....	91
5.10: a) Actual and forecasted load for hot week period, SEC, 2005	
b) Absolute error and MAPE, next day, NN.....	92
5.11: a) Actual and forecasted load for Ramadan season, SEC, 2005	
b) Absolute error and MAPE, next day, NN.....	92
5.12: a) Actual and forecasted load for summer vacation season, SEC, 2005	
b) Absolute error and MAPE, next day, NN.....	93
5.13: a) Actual and forecasted load for cold week period, SEC, 2005	
b) Absolute error and MAPE, next day, analytical model .....	94
5.14: a) Actual and forecasted load for hot week period, SEC, 2005	
b) Absolute error and MAPE, next day, analytical model .....	95
5.15: a) Actual and forecasted load for Ramadan season, SEC, 2005	
b) Absolute error and MAPE, next day, analytical model .....	95
5.16: a) Actual and forecasted load for summer vacation season, SEC, 2005	

b) Absolute error and MAPE, next day, analytical model .....	96
5.17: Average MAPE for each hour for: (a) SEC (b) Marafiq (c) USA data .....	98
5.18: a) Actual and forecasted load for cold week period, SEC, 2005	
b) Absolute error and MAPE, next day, iterative model .....	99
5.19: a) Actual and forecasted load for hot week period, SEC, 2005	
b) Absolute error and MAPE, next day, iterative model .....	99
5.20: a) Actual and forecasted load for Ramadan season, SEC, 2005	
b) Absolute error and MAPE, next day, iterative model .....	100
5.21: a) Actual and forecasted load for summer vacation season, SEC, 2005	
b) Absolute error and MAPE, next day, iterative model .....	100
5.22: a) Actual and forecasted load for cold week period, Marafiq, 2011	
b) Absolute error and MAPE, next hour, NN .....	102
5.23: a) Actual and forecasted load for hot week period, Marafiq, 2011	
b) Absolute error and MAPE, next hour, NN .....	102
5.24: a) Actual and forecasted load for Ramadan season, Marafiq, 2011	
b) Absolute error and MAPE, next hour, NN .....	103
5.25: a) Actual and forecasted load for summer vacation season, Marafiq, 2011	
b) Absolute error and MAPE, next hour, NN .....	103
5.26: a) Actual and forecasted load for cold week period, Marafiq 2011	
b) Absolute error and MAPE, next hour, analytical model .....	104
5.27: a) Actual and forecasted load for hot week period, Marafiq, 2011	
b) Absolute error and MAPE, next hour, analytical model .....	105
5.28: a) Actual and forecasted load for Ramadan season, Marafiq, 2011	
b) Absolute error and MAPE, next hour, analytical model .....	105
5.29: a) Actual and forecasted load for summer vacation season, Marafiq, 2011	
b) Absolute error and MAPE, next hour, analytical model .....	106
5.30: a) Actual and forecasted load for cold week period, Marafiq, 2011	
b) Absolute error and MAPE, next day, NN.....	107
5.31: a) Actual and forecasted load for hot week period, Marafiq, 2011	
b) Absolute error and MAPE, next day, NN.....	108
5.32: a) Actual and forecasted load for Ramadan season, Marafiq, 2011	
b) Absolute error and MAPE, next day, NN.....	108
5.33: a) Actual and forecasted load for summer vacation season, Marafiq, 2011	
b) Absolute error and MAPE, next day, NN.....	109
5.34: a) Actual and forecasted load for cold week period, Marafiq, 2011	
b) Absolute error and MAPE, next day, analytical model .....	110
5.35: a) Actual and forecasted load for hot week period, Marafiq, 2011	
b) Absolute error and MAPE, next day, analytical model.....	110

5.36: a) Actual and forecasted load for Ramadan season, Marafiq, 2011	
b) Absolute error and MAPE, next day, analytical model .....	111
5.37: a) Actual and forecasted load for summer vacation season, Marafiq, 2011	
b) Absolute error and MAPE, next day, analytical model .....	111
5.38: a) Actual and forecasted load for cold week period, Marafiq, 2011	
b) Absolute error and MAPE, next day, iterative model .....	112
5.39: a) Actual and forecasted load for hot week period, Marafiq, 2011	
b) Absolute error and MAPE, next day, iterative model .....	113
5.40: a) Actual and forecasted load for Ramadan season, Marafiq, 2011	
b) Absolute error and MAPE, next day, iterative model .....	113
5.41: a) Actual and forecasted load for summer vacation season, Marafiq, 2011	
b) Absolute error and MAPE, next day, iterative model .....	114
6.1: A typical AIM abductive network model showing various types of functional elements .....	118
6.2: a) Actual and forecasted load for year 1990, Seattle, USA	
b) Absolute error and MAPE, next hour, NN model .....	122
6.3: a) Actual and forecasted load for year 1990, Seattle, USA	
b) Absolute error and MAPE, next hour, Hybrid analytical model .....	123
6.4: Actual and forecasted load profile for Wednesday 8 Aug, 1990 (working day) using:(a) abductive networks (b) ANN (c) hybrid analytical model .....	128
6.5: Actual and forecasted load profile for Saturday 11 Aug, 1990 (working day) using:(a) abductive networks (b) ANN (c) hybrid analytical model .....	129
6.6: Actual and forecasted load profile for Sunday 12 Aug, 1990 (working day) using:(a) abductive networks (b) ANN (c) hybrid analytical model .....	130
6.7: Actual and forecasted load profile for Monday 3 Sep, 1990 (working day) using:(a) abductive networks (b) ANN (c) hybrid analytical model .....	131
6.8: Actual and forecasted load profile using iterative model for:(a) Wednesday 8 Aug, 1990 (b) Saturday 11 Aug, 1990 (c) Sunday 12 Aug, 1990 (d) Monday 3 Sep, 1990 .....	132
6.9:(a) Labor Day load profile for years 1985-1990 (b) Similarity of Labor Day load profile for years 1985-1989 (c) Ac components for Labor Day load profile for years 1985-1989 .....	134
6.10: Actual Labor Day for 1990 decomposed to its dc and ac components.....	135

## **THESIS ABSTRACT**

**NAME** : Ahmad Abdulaziz Al-Harbi  
**TITLE OF STUDY** : Residential Saudi Load Forecasting Using Analytical  
Model and Artificial Neural Networks  
**DEGREE** : Master of Science  
**MAJOR FIELD** : Electrical Engineering  
**DATE OF DEGREE** : April 2012

In recent years, load forecasting has become one of the main fields of study and research. Short Term Load Forecasting (STLF) is an important part of electrical power system operation and planning. This work investigates the applicability of different approaches; Artificial Neural Networks (ANNs) and hybrid analytical models to forecast residential load in Kingdom of Saudi Arabia (KSA). These two techniques are based on model human modes behavior formulation. These human modes represent social, religious, official occasions and environmental parameters impact. The analysis is carried out on residential areas for three regions in two countries exposed to distinct people activities and weather conditions. The collected data are for Al-Khubar and Yanbu industrial city in KSA, in addition to Seattle, USA to show the validity of the proposed models applied on residential load. For each region, two models are proposed. First model is next hour load forecasting while second model is next day load forecasting. Both models are analyzed using the two techniques.

The obtained results for ANN next hour models yield very accurate results for all areas while relatively reasonable results are achieved when using hybrid analytical model. For next day load forecasting, the two approaches yield satisfactory results. Comparative studies were conducted to prove the effectiveness of the models proposed.



## خلاصة الرسالة

الإسم : أحمد عبد العزيز مبيريك الصبحي الحربي

عنوان الرسالة : التنبؤ بالأحمال السكنية في السعودية باستخدام النموذج التحليلي

و الشبكات العصبية الاصطناعية

التخصص : هندسة كهربائية

تاريخ المناقشة : أبريل 2012

أصبح التنبؤ بالأحمال الكهربائية في السنوات الأخيرة أحد أهم مواضيع البحث و الدراسة. هذا العمل يدرس إمكانية تطبيق طرق مختلفة للتنبؤ بالأحمال على المدى القصير لمناطق سكنية في المملكة العربية السعودية. أقترح طريقتان في هذا العمل و هي النموذج التحليلي و الشبكات العصبية الاصطناعية. أقترح نموذجان في كل طريقة و هما التنبؤ بالأحمال السكنية في الساعة القادمة و في اليوم القادم. اعتمدت الطريقتان على دراسة نشاطات الناس اليومية كالمناسبات الاجتماعية و الدينية و المناسبات الرسمية بالإضافة إلى الظروف المناخية. أجريت الدراسة على ثلاث مناطق سكنية في دولتين مختلفتين خاضعة لظروف مناخية و تصرفات بشرية مختلفة. تم جمع بيانات لمناطق سكنية من مدينة الخبر و مدينة ينبع الصناعية في المملكة العربية السعودية بالإضافة لبيانات من مدينة سياتل في الولايات المتحدة الأمريكية و ذلك لإثبات قابلية تطبيق النماذج المقترحة على الأحمال السكنية. أظهرت الدراسة نتائج دقيقة جدا للتنبؤ بالأحمال للساعة القادمة باستخدام الشبكات العصبية بينما توصل لنتائج مرضية باستخدام النموذج التحليلي. بالنسبة للتنبؤ بالأحمال لليوم القادم فقد أظهرت الدراسة نتائج مرضية باستخدام الطريقتين. في النهاية أجريت مقارنة بين النتائج المتوصل إليها في هذا العمل مع أحد الأبحاث المنشورة باستخدام طريقة أخرى و ذلك لإظهار فعالية النماذج المقترحة.

# **CHAPTER 1**

## **INTRODUCTION**

### **1.1 Overview**

In recent years, load forecasting has become one of the main fields of study and research. Electric power demand is growing rapidly throughout the world. The electricity industry is significantly affected by weather conditions and human behaviors both in terms of the operation of the network infrastructure and electricity consumption.

Power load study has been an important task for utilities to provide the necessary information of demand side to improve the accuracy of load forecasting. When the increase of peak demand occurs, it will cause some serious problems. To prevent the excess of load demand, various interruptible load control strategies have

been performed. These strategies are the kind of post control and the best way is to control and prevent it beforehand. [1]

For the applications of power flow analysis, it is important to predict the power demand of all loads within the network. This prediction is known as a load forecasting. The accurate forecasts are an important tool for power system planners to do several tasks such as economic scheduling of generating capacity, fuel purchasing scheduling, load switching, and infrastructure development. Load forecasting, however, is a difficult task because the load consumption is affected by many factors like weather conditions, holidays, economy situation, and social people activities. Load forecasts are extremely important for financial institutions, energy suppliers, and other participants in electric energy generation, transmission, distribution, and markets.

## **1.2 Classification of Power System Load Forecasting**

The forecasts are divided into three categories:

- Short term which is based on forecasting from one hour to one week ahead based on time factors and accurate weather prediction.
- Medium term is from one week to one year ahead.
- Long term is based on more than one year ahead forecasting, predominantly based on historical load and weather data as well as economic and demographic factors.

### **1.2.1 Short Term Load Forecasting (STLF)**

These forecasts are normally needed for day by day economic operations of power generation plants. STLF can be performed in one of two modes which are online and offline forecasting. This division stems from the areas of application of the

load predictors. Offline load forecasting is primarily implemented in the scheduling of the large generating units of which the startup times may vary from few hours ahead to few days ahead. The scheduling process is termed unit commitment and ensures that there is sufficient operating generation capacity to meet the variable load demand with specified reliability. When load forecasting is poor, incorrect scheduling may happen. This results in higher daily operational cost caused by use of higher-cost quick-start units in the event of under scheduling or, alternatively, resulting in the uneconomic operation of large generating units in the event of over scheduling. [2]

In Online operation of a power system, the economic load dispatching to various generating units, makes the generating mix dependent on calculations to minimize the cost function, which is based on the characteristics of the generating units. These calculations are based on values of load demand predicted few hours in advance, and as such the optimum generating mix is dependent on the accuracy of the online forecasts. In STLF, the future load on the power system is predicted by extrapolating a predetermined relationship between the load and its affecting factors. Determining this relationship is a two stage process requiring identifying the load and the related variables relationship, and quantifying this relationship through the use of a suitable parameter estimation technique. A prerequisite to the development of an accurate load-forecasting model is an in-depth understanding of the characteristics of the load to be modeled. This knowledge of the load behavior is gained from experience with the load and through statistical analysis of past load data. Utilities with similar climatic and economic environments usually experience similar load behavior, and load models developed for one utility can usually be modified to suit another. The load supplied by a power system is dynamic in nature and directly reflects the activities and

conditions in the surrounding environment. This load can be separated into a standard or base load, a weather dependent load, and a residual load. [3]

### **1.2.2 Mid Term Load Forecasting (MTLF)**

Outage scheduling and maintenance of plants and networks are often roofed in these types of forecasts. Also, MTLF is used for estimating fuel (storage) requirements and for planning the execution of maintenance programs. For MTLF, the main influence factors are meteorological and casual. The influence of economic parameters is negligible due to the time horizon that is too short for the economics effects to be felt. [4].

### **1.2.3 Long Term Load Forecasting (LTLF)**

It is primarily intended for capital investments, capacity expansion plans, and corporate budgeting. LTLF is usually complex in nature because of future uncertainties such as economic situation, political factors, per capital growth, scheduling the construction of new generation facilities and in the development of transmission and distribution systems. An overestimate of long-term electricity demand will result in substantial wasted investment in the construction of excess power facilities, while an underestimate of demand will result in insufficient generation and unmet demand. [5]

In summary, the required forecasts can range from few minutes to over forty years. They can be divided based on the time horizon into three types, Table 1.1 shows the types of forecast and their applications.

Table 1.1 Different types of forecasting and their applications

Forecasting Type	Time Range	Applications
Short	Few minutes to one week	Daily operation, plant scheduling, load dispatching and reserve allocation
Medium	One week to a year	Fuel and maintenance planning
Long	One year and more	System planning, infra-structure developments

### 1.3 Prerequisites of a Good STLF System

Most of demand or load management programs used by electric utilities comprise STLF units. Every utility intends to have a reliable STLF system for economical operations of power systems. The reliability and robustness of the system primarily depend on the accuracy of the forecasts. Though, there are other important requirements for a good STLF system. These requirements include fast speed, accuracy, automatic data access, friendly interface, timely forecast, automatic performance evaluation of the obtained forecast and automatic bad data detection and forecasting report generation. [6]

### 1.4 Saudi Load Characteristics

Kingdom of Saudi Arabia (KSA) is a developing country. The rapid urbanization, economic developments, the substantial increase in oil revenue and the new infrastructure projects cause the electricity demand to grow rapidly, especially during the last decade. Generation of electricity, transmission and distribution in KSA are very important subjects for the decision makers in the Kingdom making the studies and research in the field of electricity demand to be very useful. Also, substantial savings can be achieved through suitable timing and proper selection of the main

generation and transmission works. So, the expansion in projects and developments in KSA have clearly affected the electric generation and consumption trend. As shown in figure 1.1, the yearly peak loads for a residential area in Eastern Province in KSA for the period from 2001 to 2005, show how the demand was rapidly increasing.

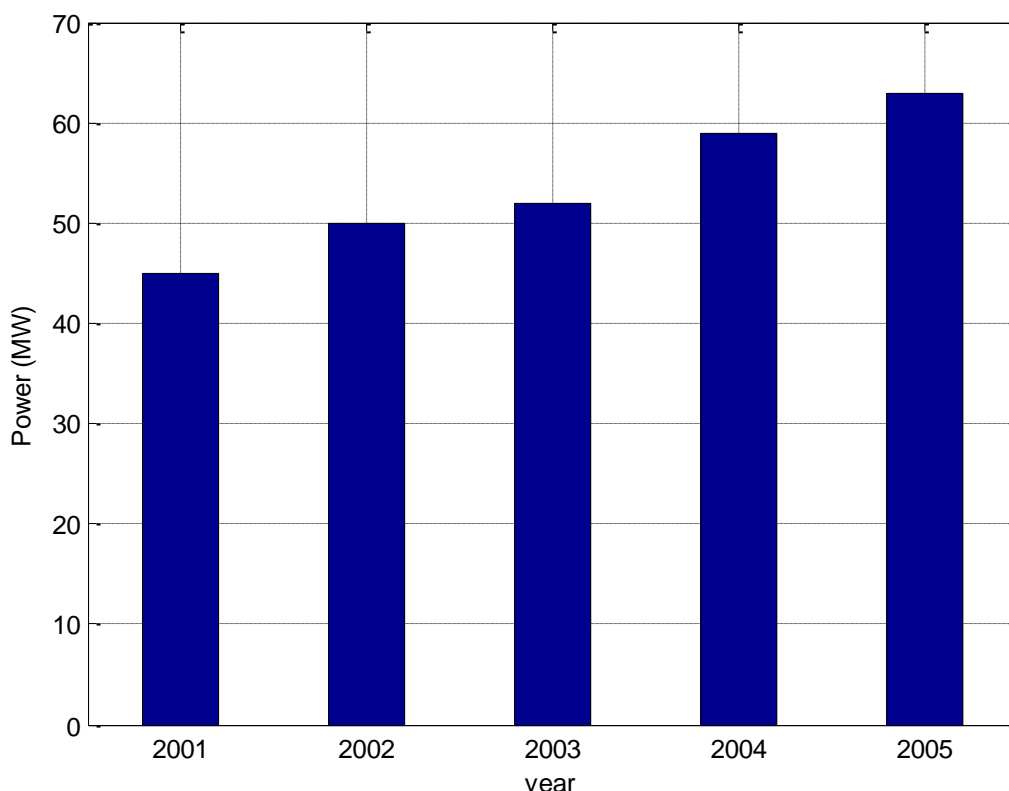


Figure 1.1: The annual peak load for a residential area in Al-khubar, Agrabiah district

The weather in KSA is characterized by its high temperature values in summer, except for some places like southern region, and low temperature values in winter. The humidity is normally noticed in the east and west coasts where it reaches to 100 %. So, the load consumption is mainly affected by cooling appliances. Moreover, two types of calendars are available, namely, Hijra calendar which is the main calendar in KSA and Gregorian calendar. In Hijra calendar, there is the most important month for Muslims which is Ramadan. In Gregorian calendar, the known seasons of the year are available which are: winter, spring, summer and fall. In addition, there is a difference of 10 to 11

days between the Hijra and the Gregorian calendars and because of that; there is an overlapping between the two calendars seasons. However, in other countries like USA, Seattle, the very low temperature values in the winter lead to many uses of heating loads causing high levels of load consumption. As a result, the type of the load is mainly heating load. This is clearly shown in figure 1.2 which shows the load consumption and temperature profiles for the residential area in Al-Khubar, year 2002 where the maximum demand has reached 50 MW at temperature 38 °C. Also, figure 1.3 shows the load consumption and temperature profiles for an aggregated load area in USA, Seattle, year 1989. The maximum demand has reached 4245 MW at temperature -11.27 °C. It can be concluded that the temperature is the main influencing factor on load consumption for all types of loads.

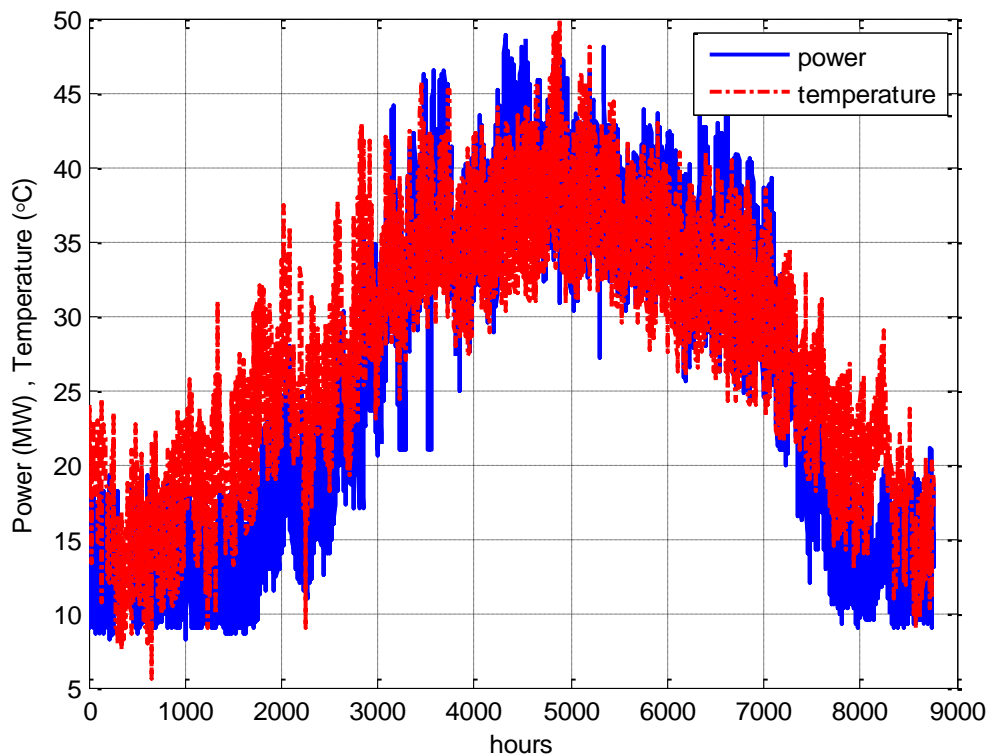


Figure 1.2: Power and temperature profiles for Agrabia substation, 2002



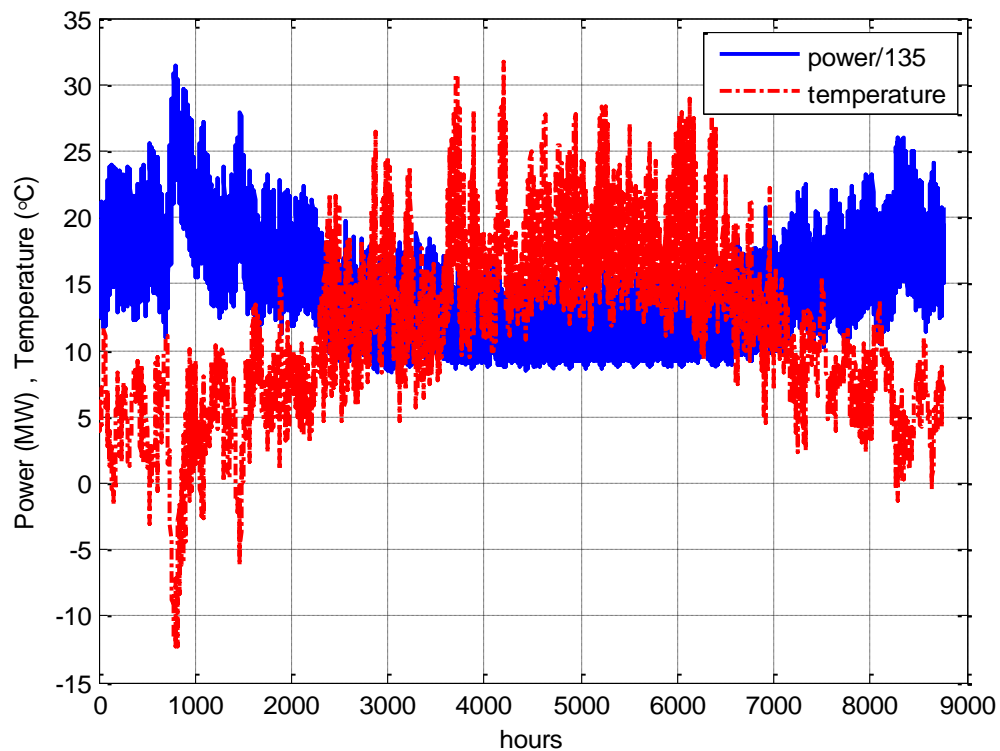


Figure 1.3: Power and temperature profiles for USA, Seattle, 1989

In figure 1.2, the increase in the load is caused by the increase in the temperature values due to heavy uses of air conditioners and cooling apparatus overall the year and it can be concluded that the load is proportionally related to the temperature, i.e. when the temperature increases, the load consumption increases. By contrast, in figure 1.3, the increase in the load is caused by the decrease in the temperature because of using of heating appliances where very low temperature values are reached. So, there is an inversely proportional relation between load and temperature. i.e., when the temperature decreases, the load increases.

So, in summary, the problem of KSA load forecasting is very complicated and challenging. This is because the fact that there are many complex factors that affect the amount of the needed load each season and each year. Some of these factors are:

- The rapid commercial, economic and population growth of the Kingdom.
- The large diversity of maximum and minimum temperature values over seasons. Normally, the high temperature period (July and August) is characterized by high ambient temperatures.
- All special holidays and school days depend on the Hijra calendar which is a lunar calendar, constitutes a major factor that has a noticeable impact on the load consumption. The largest religious festivals in the country are: Ramadan (fasting month for Muslims), Eid Al-feter that marks the end of Ramadan, and first part of the month of Dul-Hijjah in which Hajj pilgrimage to Makah takes place. In these events, load consumption is subjected to significant changes. For example, during Ramadan month, the load is usually increased due to the increase in some residential and commercial activities. Moreover, religious holidays and schools are cyclic and irregular in some sense. The formation of these factors makes the process of demand forecasting difficult and more difficult than countries that have common behaviors for people. [7]

### **1.5 Scope and Objective of the Work**

- This work studies the residential short term load forecasting (STLF) for different types of loads under several human modes of behaviors
- To develop a hybrid analytical model function of influential factors to reflect these behaviors.
- To reach an intelligent model for these behavioral variations using Artificial Neural Networks (ANN) model.

The applicability of different ANN models on STLF will be studied. The models are divided into two classes: model for next hour load forecasting and the other is for next day load forecasting for three different load behaviors in two countries. The analysis is carried out on residential areas in Eastern Province and in Yanbu industrial city in KSA and in an aggregated load area in Seattle, USA.

Different patterns of load behaviors are presented in this study. For example, the residential area in Eastern Province is characterized by its high temperature and humidity values. Also, but in lower values, Yanbu industrial city has almost similar weather characteristics to Eastern Province. So, this is studying cooling load behaviors. However, Seattle is specialized by its very low temperatures in winter and medium in summer making the study to be mainly on heating load behavior.

Another difference is the evacuating behavior for population in Yanbu industrial city where in vacations periods most of people leave this industrial city and travel to their original cities. Also, working days for companies is highly noticed in addition to school days.

In this work, we are interested in analyzing load models for three sources of data exposed to different weather conditions and human behavior. The analyses will be done in two different ways; ANN and hybrid analytical models based on actual realistic model behavior of residential load. This work concentrates more on STLF based on residential modes analyses which are group of days that have similar behavior like Ramadan, cold days, hot days, holidays...etc. Also, the impact of surrounding environmental conditions will be studied.

## **1.6 Structure of the Work**

This study is arranged according to the following structure:

Chapter two gives an overview of different techniques used in STLF. Also, some important published papers in the field of STLF will be overviewed and discussed. Chapter three will talk about data analysis, modes classification and sorting every special behavior to modes and analyzing them. Three different load behaviors in two different countries are presented in this chapter. In chapter four, the approaches used in this study are analyzed. It presents the concept of Fourier Transform analyses and its applications, ANNs analysis including Neuron Model, Network Architectures and learning. Also, analytical hybrid model and regression analyses are presented. Chapter five shows the proposed model and the results. Chapter six shows a comparison of the method used in this study with another published paper method applied to the same data. Finally, conclusion and recommendations are shown in chapter seven.

## **CHAPTER 2**

### **LITERATURE REVIEW**

Electrical load forecasting has been extensively studied in the past few decades. Several methods which are varying in the complexity of estimation approaches and functional forms have been proposed to improve the accuracy of load forecasting. The forecasted load system is a random process composed of thousands of individual components. So, the range of possible techniques of the forecasting is wide. The methods of STLF can be categorized into two main categories: artificial intelligence methods and statistical methods. Artificial intelligence methods are trying to imitate human brains and their way of thinking and reasoning to get the information from the past experience and forecast the future load, while in statistical methods, equations can be obtained which show the relationship between load (dependent

variable) and its relative affecting parameters (independent variables) after training the historical load data.

In artificial intelligence, the models include Fuzzy Logic Inference, Expert systems, wavelet transform and artificial neural network (ANN), which will be introduced in chapter 4. However, in statistical methods, the models include multiple linear regression, similar day approaches, support vector regression (SVR), stochastic time series and state space models. Moreover, other methods were used like grey models, data mining methods and machine learning. In this section, an overview of some main various methodologies developed in recent years for STLF is carried out.

## **2.1 Fuzzy Logic**

In the mid of 1960s, the term “fuzzy logic” is emerged in the theory development of fuzzy set which is pioneered by Dr. L.A. Zadeh. A fuzzy logic model is a logical-mathematical approach which is based on an “IF-THEN” rule system that mimics the thinking way of the human in computational form. In General, a fuzzy rule system has four modules:

- Fuzzification of the input which is a process that transforms the “crisp” into a fuzzy input.
- Fuzzy rules, it is an IF-THEN logic statement which connects the input to the output variables.
- Fuzzy inference which is a process that elaborates and combines rule outputs.
- Fuzzification of the output which is a process transforming the fuzzy output into a crisp output. [8]

Fuzzy logic method has gained a wide recognition and a variety of products ranging from air conditioners, washing machines, cameras to medical instrumentation, industrial process control, system identification, signal processing and speech recognition. Specifically in load forecasting, fuzzy rules based on demand forecasts must be developed to provide domain specific information to improve the non-linear models. [6]

In power systems applications, fuzzy systems have been applied in diverse fields including stability evaluation, optimal power flow and dynamic dispatch. Zeng yanfei and Wu Yinbo [9], proposed STLF model based on fuzzy rule and Backpropagation Neural Network (BPNN). The load forecasting has been divided into basic load component which is completed by the BPNN; and the temperature and holiday load component which is completed the fuzzy logic.

In reference [10] by Ghanbari et al., the study used three of the most successful AI techniques in STLF area which are Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Networks (ANN) and Genetic Algorithm (GA). To improve forecasting accuracy, all these techniques are equipped with preprocessing concept, and effects of this concept on performance of each AI technique are investigated. The obtained results show that data preprocessing can significantly improve the AI techniques performance.

In 2008, Pandian et al. [11] presented a fuzzy logic for STLF where the inputs are the temperature and the time of day whereas the output is the load. There are 4 membership functions for the temperature, 8 for the time of day, and 8 for the load. The proposed method is tested using the data from a power station in India.

## 2.2 Expert Systems

This method is derived by system developers and experts through experience and close interactions. Its main concept is to manipulate and encapsulate high level knowledge in an attempt to imitate the behavior of an expert. It does not require any specific model hierarchy or a historical trend. The forecasting procedure is rather encapsulated by rules that are derived from interviews with human expert. Once these rules are defined clearly, the uncertainties which may affect the load would be taken care of, thus this technique should be reliable. [6]

Ho et al [12] proposed a knowledge-based expert system for the STLF of the Taiwan power system. Operators' knowledge and the hourly observation of system load over the past five years are employed to establish eleven day-types. Weather parameters were also considered.

In [13], Rahman and Hazim developed a site-independent technique for STLF. Knowledge about the load and its affecting factors is extracted and represented in a parameterized rule base which is complemented by a parameter database that changes from site to site. The method is tested in different sites in the United States with low forecasting errors. The load model, the rules and the parameters have been designed without using specific knowledge about any particular site. Results are improved if operators at a particular site are consulted.

Expert systems are usually used in conjunction with other load forecasting techniques. Kim et al. in [14] used a two-step method to forecast the load for the Korea Electric Power Corporation. First, an ANN model forecasts the base load, then a fuzzy expert system model modifies the base load by considering temperature changes and



the load variation of the same special day in the previous year. However, this system had difficulties in forecasting the load over long weekends and consecutive holidays.

Srinivasan et al. [15] combined fuzzy logic, ANNs and expert systems in a highly automated hybrid STLF approach with Kohonen's self-organizing feature map and unsupervised learning.

### **2.3 Particle Swarm Optimization (PSO)**

Particle Swarm Optimization is a global minimization technique for dealing with problems in which a best solution can be represented as a point or and a velocity. Each particle assigns a value to the position they have, based on certain metrics. They remember the best position they have seen, and communicate this position to the other members of the swarm. The particles will adjust their own positions and velocity based on this information. The communication can be common to the whole swarm, or be divided into local neighborhoods of particles. [16]

Azzam et al [17] present a new method to model STLF in which STLF-ANN forecaster is trained by optimizing its weights using swarm intelligence. They proposed smaller ANN models of STLF based on hourly load data and adjust its weights through the use of PSO algorithm. The technique gives better trained models able of performing well over varying time window and results fairly accurate forecasts.

A new PSO approach is proposed by Huang et al. [18]. It is about identifying the autoregressive moving average with exogenous variable (ARMAX) model for one day to one week ahead hourly load forecasts. The proposed PSO has been tested on the different types of Taiwan Power (Taipower) load data and compared with the evolutionary programming (EP) algorithm and the traditional search-based stochastic

time series method. Testing results indicate that the proposed PSO has superior convergence characteristics, high-quality solution, and shorter computation time.

In 2008, Wang et al [19] presented a hybrid approach of NN with PSO training algorithm to develop the predictions accuracy. The technique is applied to forecast daily peak loads of the Beibei, Chongqing electricity system based on past available data for electricity load demand. Traditional BP-NN and ARMA model are investigated as comparison basis. The experimental results show that the proposed method could achieve better prediction performance.

## **2.4 Wavelets**

Wavelet (WT) is a linear transformation much like the Fourier transforms. However, it allows localization of time of different frequency components for a given signal; windowed Fourier transform, also partially achieves the same goal, but the fixed width windowing function is a limitation. In the case of the WT, the analyzing functions called wavelets which adjust the time width to the frequency in such a way that high frequency wavelets will be very narrow and lower frequency ones will be broader. [20]

Yao et al. [21] proposed novel approach for STLF by combining the wavelet transform and NNs. Since electrical load at any specific time is usually assumed to be a linear combination of different components, from the signal analysis point of view, load can be also considered as a linear combination of different frequencies. Each component of load can be represented by one or several frequencies. The process decomposes the historical load into an approximate parts associated with low frequencies and several detailed parts

associated with high frequencies through the WT. Then, the forecast of the part of future load is developed using a neural approximation.

Nengling et al. [22] presented techniques of applying WT into combined model for STLF. It is shown that the load can be described by the corresponding components in the time frequency domain. It is found that even the model performs well for certain load components; it will be not suitable for other components. This is because it cannot consider every factor. Therefore, different combined forecasting approaches are selected in each scale. The forecasting results can be obtained by reconstruction of these results in different scales. Case studies show that the proposed technique can offer high forecasting accuracy.

In [23], Bashir and El-Hawari presented the application of the wavelet neural networks (WNNs) to STLF. The WNN has fast learning convergence and much higher generalization ability than a multilayer feed forward neural network. The network is trained by the 3-layer BP algorithm by learning the nonlinear relationship between network input and output. The results of the network have been compared with an ANN and show an improved forecast with fast convergence.

## **2.5 Regression Methods**

Regression analysis is one of the most common and popular statistical modeling tools used. It is a technique that treats one variable as a function of another. Regression analysis gives information about the relationship between a response (dependent) variable and one or more (predictor) independent variables to the extent that information is contained in the data. It can be used to consider more complex

relationships by using more than two variables or combinations of different order equations. The aim of this technique is to express the response variable as a function of the predictor variables. The duality of fit and the accuracy depend on the data used. So, non-representative or improperly compiled data will result in poor fits and conclusions. Therefore, to reach to effective use of regression analysis one must,

- investigate the data collection process,
- discover any limitations in data collected, and
- restrict conclusions accordingly.

Once a regression analysis relationship is obtained, it can be used to predict the response variable values, identify which variables that affect the response mostly, or verify hypothesized causal models of the response. Each predictor variable value can be assessed through statistical tests on the estimated coefficients (multipliers) of the predictor variables. [24]

The load model using regression method is expressed in the form as:

$$y(t) = a_0 + \sum_{n=1}^n a_n x_n(t) + a(t) \quad (2.1)$$

Where:

$y(t)$  is the electrical load.

$x(t)$  is explanatory variables correlated with  $y(t)$ .

$a(t)$  is a random variable with zero mean and constant variance.

$a(n)$  represents regression coefficients.

The explanatory variables of this model are identified on the basis of correlation analysis on each of these independent variables with the load variable. Experience about the load to be modeled gives initial identification of the

suspected influential variables. Regression coefficients estimation is usually found using the least square estimation technique. Statistical tests are performed to determine the importance of these regression coefficients. The t-ratios resulting from these tests determine the significance of each of these coefficients, and correspondingly, the significance of the associated variables with these coefficients [25].

Slobodan Ružić [26], proposed a regression-based adaptive weather sensitive STLF algorithm which is developed and implemented in Electric Power Utility of Serbia. The model parameters are calculated and updated automatically using realized data in the identification period, which is similar to conditions of the expected period in the forecasted day, by using the Euclidean distance to measure the similarity.

AI-Kandari, et al. [27] proposed two possibility models for regression to forecast the load of 24-hour ahead in summer and winter seasons respectively. A multi linear regression model for STLF depends on how well the regression function fits the data, considering in addition to temperature, other related weather factors such as humidity and cloud cover which are presented in [28].

## **2.6 Similar Days Approach**

This approach is based on searching for historical data for days within one, two or three years with similar characteristics to the forecasted day. Similar characteristics include weather, day of the week and the date. The load of a similar day is considered as a forecast. Instead of a single similar day load, the forecasting can be a linear combination or regression procedure that can include many similar days. The trend coefficients can be used for similar days in the past years. [29]

In [30], the Mandal et al. presented a practical approach for STLF, using ANN combined similar days approach. Euclidean norm with weighted factors is used to evaluate the similarity between the forecasted day and searched previous days. On the bases of similar days approach, load curve is forecasted using information of the days which are similar to weather conditions of the forecasted day. The obtained results confirm that ANN-based proposed approach provides reliable forecasts for several-hour-ahead load forecasting.

In 2005, Yu Jun He et al. [31] presented a new approach that is capable for choosing the training set for the NN. It uses similarity degree parameter to identify the suitable historical load data as training set for the NN. This similar days selection strategy can efficiently avoid the problem of holiday and sudden variations in the influential factors, that make some historical load data unlikely for training the network. The validity of the model has been tested using Hebei province daily load data. Using the presented model, the enhanced forecasting accuracy and learning potency can be achieved.

## **2.7 Time Series**

A time series is a set of data generated sequentially in time. The time series models assume that in the absence of major disruptions to critical factors of a recurring event, the data of this event in the future will be related to that of the past events and can be expressed by models developed from the past events. [32]

In [33], Amjady uses ARIMA for tuning the unknown parameters by using previous values of the load demand and previous values of the inputs. After that, the model is used to forecast the load demand for unknown points of the operating system.

In 2005, Marcelo et al. [34] use a periodic auto regression model for developing a set of 24 “seasonal” equations with 48 parameters for each one. The set of equations is extended to include exogenous variables that describe the temperature impacts and the monthly and weekly seasonal variations.

Generally, time series approaches give satisfactory results if there is no change in the load demand affecting parameters. If there is a sudden change in any of these parameters, then time series methods are not as accurate. Moreover, as there is a need to use a large amount of historical data and a large number of complex relationships, time series techniques require a significant computational time and may result in numerical instabilities [35].

Amarawickrama and Hunt in 2008 [36] presented a time series analysis of electricity demand in Sri Lanka. They studied the performance of different time series estimation approaches in terms of modeling previous electricity demand, and forecasting future electricity consumption.

## **2.8 Support Vector Machine (SVM)**

SVMs are a more recent powerful method to solve regression and classification problems. This approach was originated from Vapnik’s [37] statistical learning theory. Unlike ANNs, which attempt to define complex functions of the input feature space, SVMs perform a nonlinear mapping (by using so-called kernel functions) of the data into a high dimensional (feature) space. Then SVMs use simple linear functions to create linear decision boundaries in the new space. [38].

Chen et al. [39] proposed a SVM model to forecast daily load demand. Their program was the winning entry of the competition organized by the EUNITE network.

Jain and Satish [40] proposed new hybrid technique using SVM and ANN to forecast the next 24 hours load. The forecasted load for the next 24 hours is obtained by using four modules consisting of the Basic SVM, Peak and Valley ANN, Averager and Forecaster and Adaptive Combiner. The Basic SVM uses the historical data of load and temperature to predict the next 24 hours load, whereas the Peak and Valley ANN uses the past peak and valley data of load and temperatures respectively. The Averager captures the average variation of the load from the previous load behavior, while the Adaptive Combiner uses the weighted combination of outputs from the basic SVM and the Forecaster, to forecast the final load.

In 2002, Mohandes [41] applied SVM technique for STLF. SVM performance is compared with the autoregressive method. The results indicate that SVMs produce better results against the autoregressive method.



## **CHAPTER 3**

### **DATA ANALYSIS**

### **AND MODES CLASSIFICATION**

#### **3.1 Overview**

A sufficient period of historical data is very important to make and establish the relation between any input and output parameters. The availability of this data helps visualizing the effect of input variables on output variables. So, enough knowledge of the past is necessary for understanding what is happening in the present and what may occur in the future.

This part shows the steps used to manipulate the data, arrange and organize the parameters and presents how the data are coded and represented to reach to the desired results.

### **3.2 Data Filtering**

Actually, dealing with this large amount of data is not simple. It requires manipulating these data, sorting of all parameters and dealing with data in a suitable way. Some of the data are missing while some are repeated. So, it is important to filter the data from any noise, rearrange it and remove any abnormal points and outliers from the original data. As a first step, the collected data are checked, filtered from any noises, repetitive data are removed and the data is validated for the proposed model. For statistics practice, the data preprocessing is executed to prevent the abnormal data from affecting the accuracy of load patterns derived. This process includes: ignoring missing values, smoothing noisy data and removing the abnormal points.

### **3.3 Data Sources**

The data used in this study can be divided to three sources:

1. Data collected from Agrabia substation, which is a residential substation of the Saudi Electricity Company (SEC) in Eastern Region Branch in Al-Khubar city. The available data are for the nine consecutive years from 1998 to 2006 arranged in Excel files.
2. Data supplied by Marafiq Company for a residential area in Yanbu industrial city from year 2009 to 10 December 2011. The measured data for the two cities includes: hour, temperature in Celsius, humidity, active power in MW, arranged in tabular form. All of these parameters were measured in hourly basis.
3. The third data source consists of measured hourly load and temperature data for the Puget power utility, Seattle, USA, over the period 1 January 1985 to 31 December 1990.

A Sample day from SEC data is shown in Tables 3.1 listing the hourly data for real power in MW, temperature in Celsius and humidity in percentage.

Table 3.1: Sample day from SEC data for 1 January, 2002

h	P (MW)	T ( °C )	H (%)
1	11	19	38
2	10	19	39
3	9	19	42
4	9	19	43
5	9	19	42
6	9	18	41
7	10	18	41
8	10	18	35
9	13	18	38
10	14	19	35
11	15	23	35
12	14	24	37
13	13	24	38
14	13	24	40
15	13	24	40
16	15	23	42
17	17	22	39
18	19	21	23
19	18	21	21
20	18	21	25
21	18	20	29
22	16	20	18
23	14	21	8
24	12	21	19

## **3.4 Data Analysis**

### **3.4.1 Overview**

Electricity demand is constantly changing over the time. During one year, it may vary greatly from month to month, from day to day and from hour to hour. In forecasting analysis, factors affecting the load have to be identified clearly according to people social activities and weather variables of the forecasted area. The daily load behavior will be studied and presented. Knowing the date and its relation with load behavior and weather parameters is important. Moreover, the link between week days and weekend days with the load curves will be shown and studied. This will help visualization it for every day behavior and its relationship with weather parameters. Then, the impact of seasons on load consumption will be presented as well as the annual load profile throughout the whole year.

### **3.4.2 Load Variation**

The variation of the load with respect to time can be classified to three load patterns which are based on daily, seasonally and annually basis. The study will be done progressively during different consecutive days, then during consecutive months and then to cover the whole year. The data analyzed in this section is for SEC from years 1998 to 2000.

#### **3.4.2.1 Variation with time during the day (daily behavior):**

The load varies during 24 hours in a cyclic manner as social life and activities of the consumers depend on the time of the day such as; working hours, school hours and prayer times. As a result of that, the power consumption is varying over the whole day. Figure 3.1 shows the active power, temperature and humidity versus hours for a typical day from the residential area in Al-Khubar city, 1<sup>st</sup> February, 2000. Load drops

gradually at night and becomes minimal at the early morning. Then, with the starting of schools and working time, load starts to pick up due to the increase of people activities and temperature rising. Then, it dips at the period of lunch time. Before Asr prayer, almost all governmental facilities and schools end, and temperature starts to drop. As a result, load continues dropping till Asr prayer. After Asr prayer, the load increases due to the increase in people activities again and continues to increase till the sunset. After that, it keeps increasing gradually because of the lighting load and continuous people daily routine. This continues until Eisha prayer where the daily peak occurs almost at 19.00 and then before midnight at the time of closing all commercial activities and also the time for people to sleep, the load starts decreasing till the early morning.

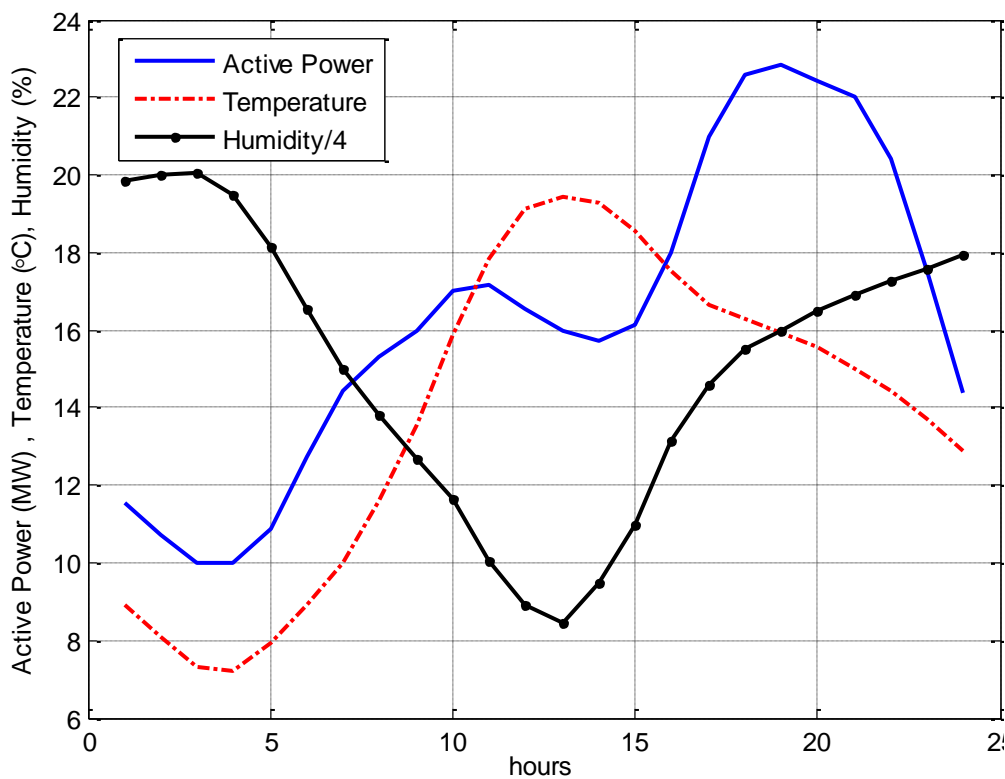


Figure 3.1: Active Power, Temperature and Humidity profiles for 1<sup>st</sup> February, 2000, SEC, Agrabia substation

### 3.4.2.2 Variation with time during the season (seasonal behavior)

Once we move from one season to another, the effect of weather variation between seasons is clearly noticed. So, the load power behavior is also changing accordingly. This is clearly shown in figure 3.2 where active power, temperature and humidity for a sample day of winter, spring, fall and summer seasons are displayed for year 2000.

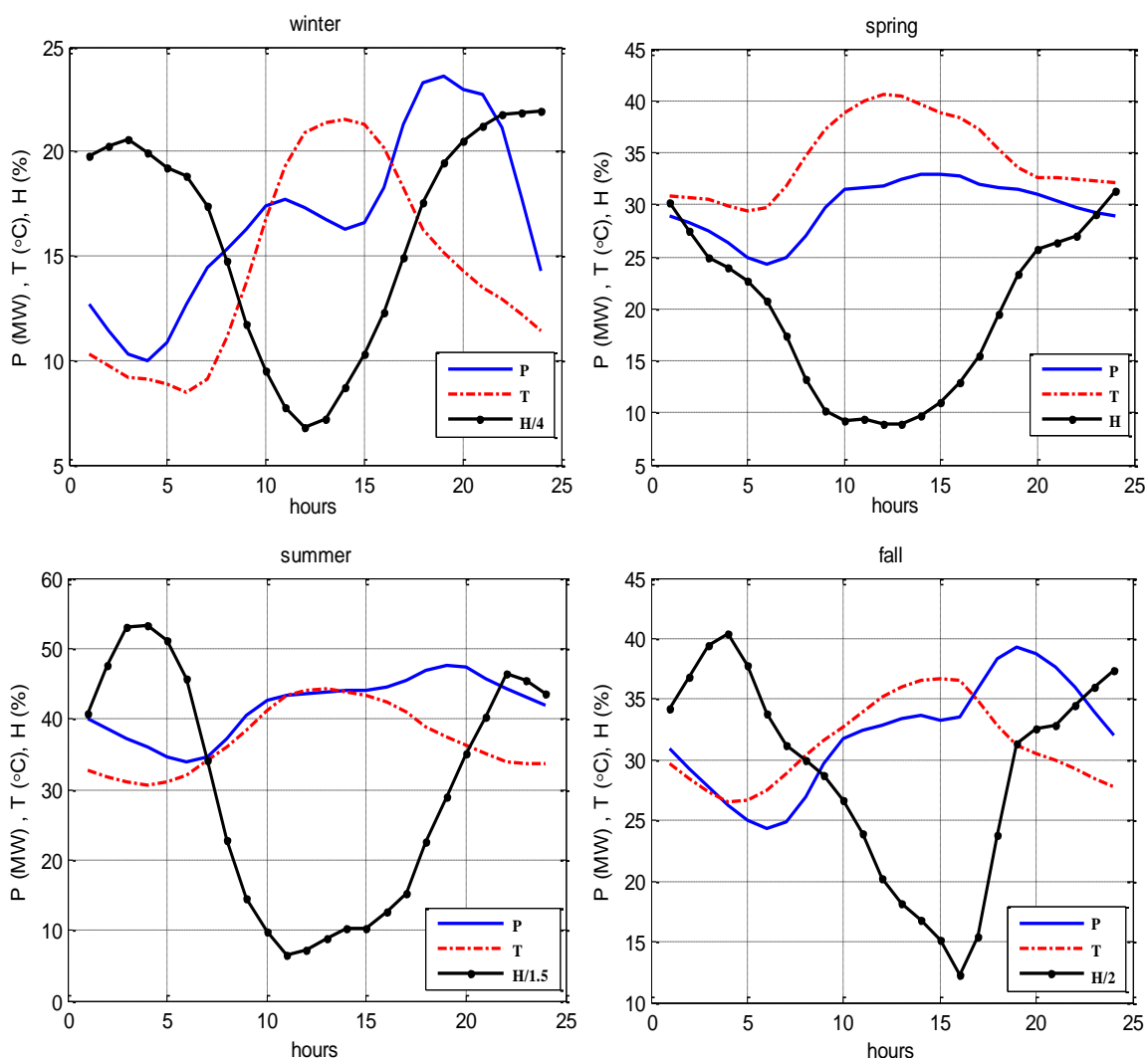


Figure 3.2: Active Power, Temperature and Humidity profiles for a sample day from each season, 2000, SEC, Agrabia substation

### 3.4.2.3 Overall variation with time during the year (annual behavior)

In addition to a daily basis variation and seasonal variation, the annual behavior of the load will be analyzed. Figure 3.3 shows respectively the active power, temperature and humidity profiles of the year 2000.

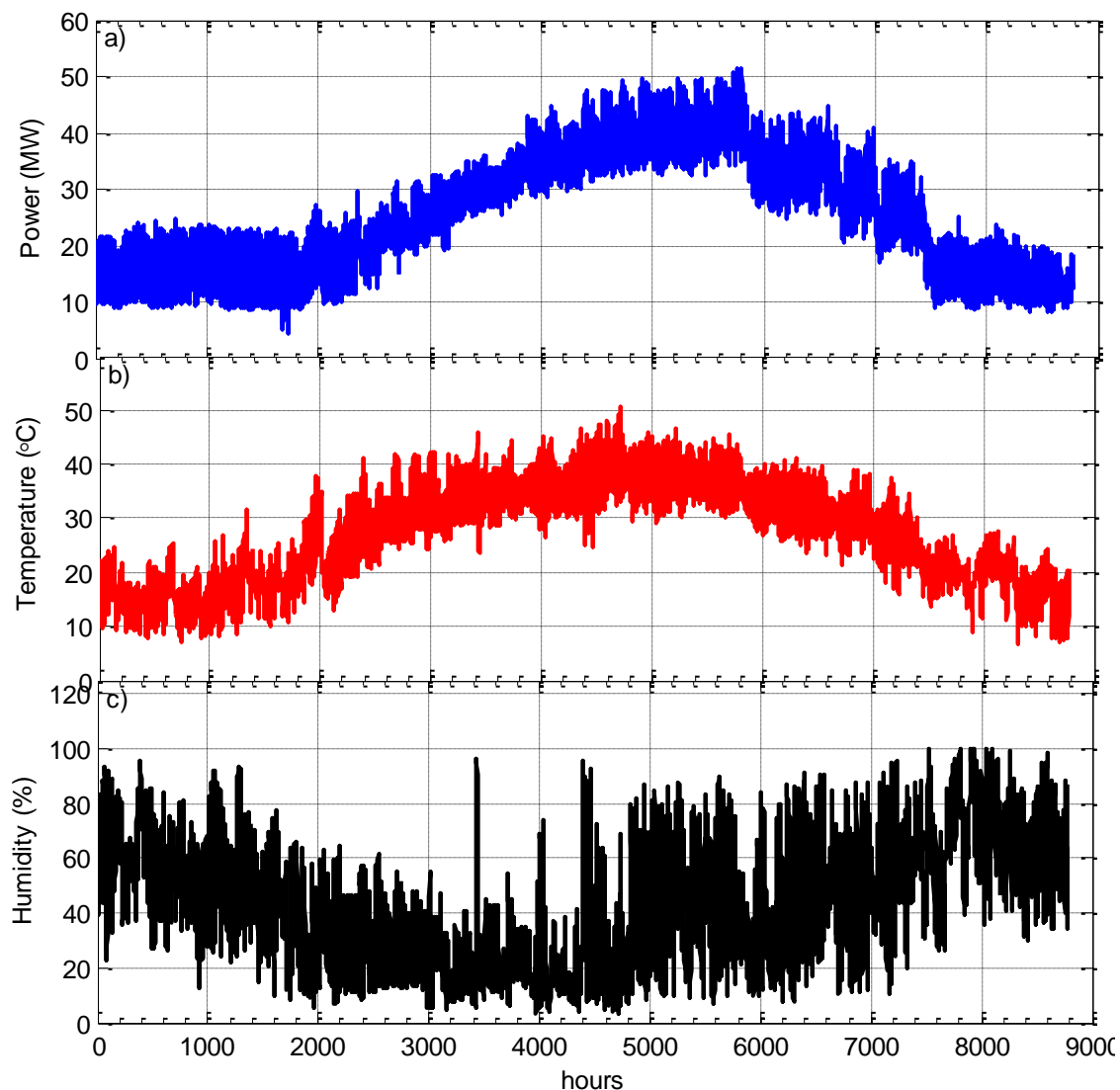


Figure 3.3: (a) Active Power, (b) Temperature and (c) Humidity profiles for year 2000, SEC, Agrabia substation

### **3.5 Special Days Analysis**

The impact of varying load consumption can be noticed at different times of the year. Consumption behavior is different from one society to another since there is a difference in working periods and vacations intervals in different countries. Normal days could be classified by normal week working days and weekend days. Also, special events days such as Ramadan days, Eids days and after Eids days are fixed by date and occur always at the same date of the Hijra calendar. If special event day happens in any normal day, its impact dominates. Daily load data can be divided into distinct behavioral patterns called behavioral modes or, simply, modes each of which has common characteristics. By looking extensively to the whole power profile for one year as shown previously in figure 3.3, it can be seen that the load consumption shape is different from day to day or from mode to mode.

### **3.6 Modes Classification**

#### **3.6.1 SEC Data**

This data is for a residential substation in Al-Agrabiah area in Al-Khubar city in the Eastern Province of KSA. The weather conditions for this area are characterized by high temperature and humidity values in summer season. Also, the nature of this area is non-evacuating population area meaning that people in this area are permanently living there. The available data from this area is from 1998 to 2006. During these nine years, two load switching were applied to the substation as seen from figure 3.4 which shows the hourly and the yearly peak load consumption, respectively for years 1998 to 2006.



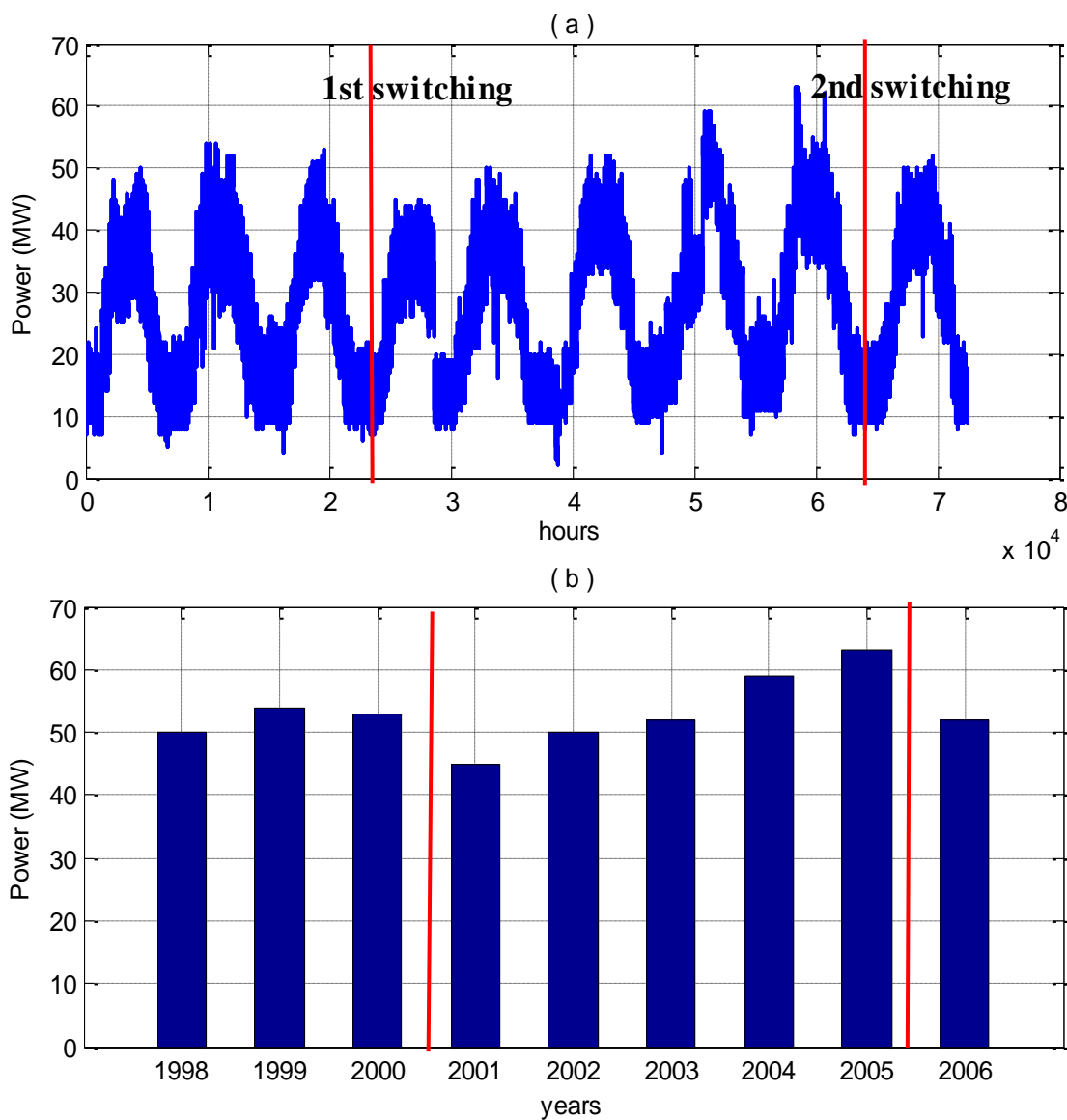


Figure 3.4: (a) Hourly load profile for years 1998 to 2006, SEC data

(b) Annual peak load for years 1998 to 2006, SEC data

As seen from figure 3.4, the residential load area was fed from the same feeder at Agrabiah substation from the period 1998 to 2000 and the measurements were taken at this feeder. At year 2000, another feeder was installed to share the load. The measurements were still taken at the original feeder. This continued until the end of the

year 2005 where another load switching was applied causing the load measured value on the original feeder to decrease in 2006.

One sample year is considered to identify the different existing modes. An extensive analysis is needed to define these modes according to the characteristics and behaviors of the area to be studied. For example, by taking a zooming view to the 11 days period from Thursday 14/1/1999 to Saturday 23/1/1999 as shown in figure 3.5, it is clear that there is a difference between these days that include many periods like Ramadan, Eid Feter day and working day.

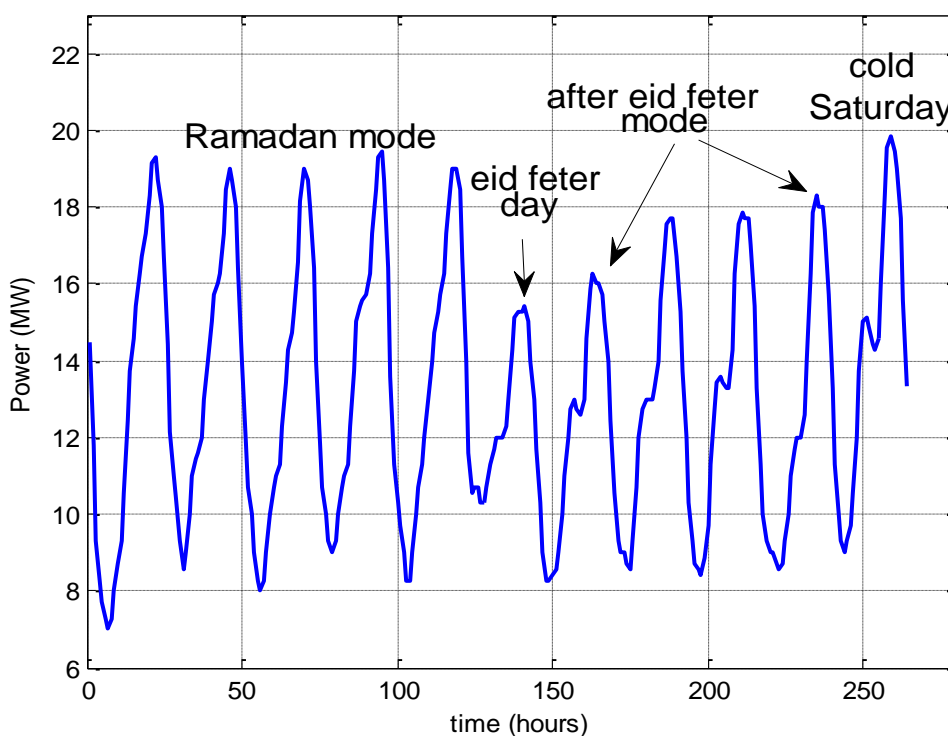


Figure 3.5: Sample 11 days for different modes in 1999

Also, a sample week starting from Saturday to Friday for 1998, 1999 and 2000 during the same period (winter period) can be seen in figure 3.6. It is obvious that there is a difference between the shape of the load on a typical weekend day, such as Friday and a working day like Saturday or Sunday.

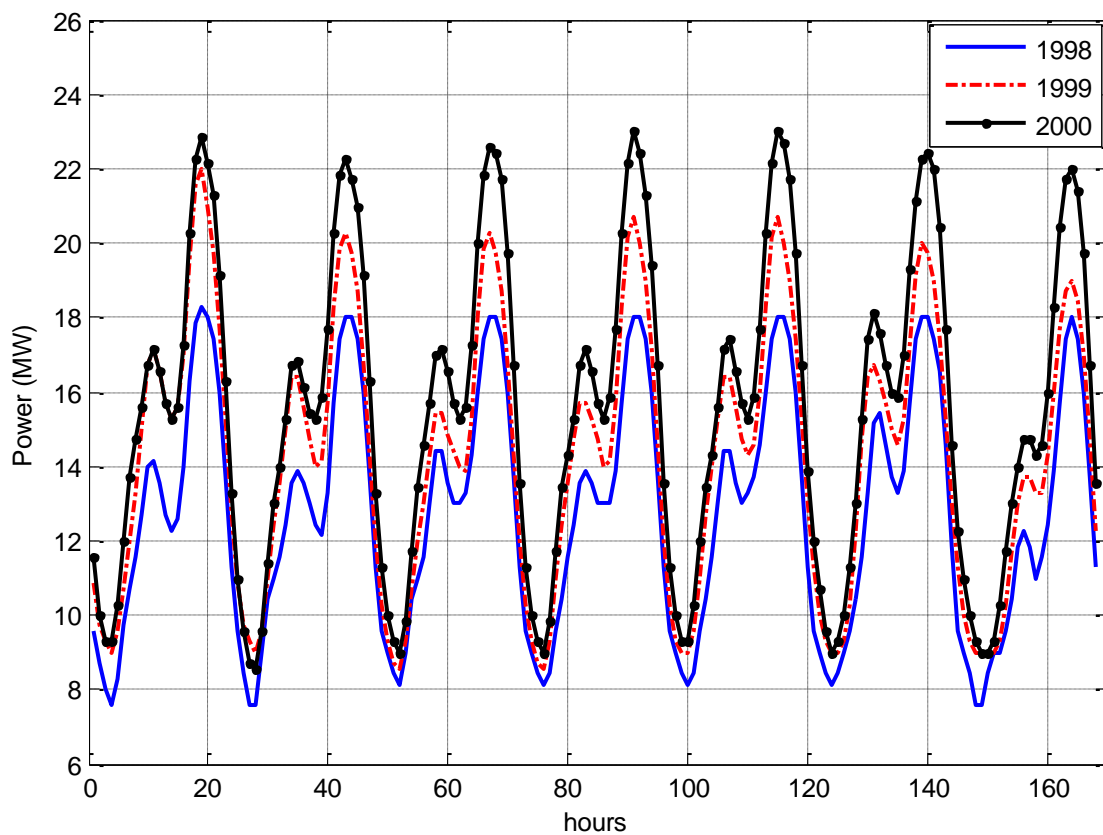


Figure 3.6: Typical cold region week, 1998, 1999 and 2000

Furthermore, there is a clear distinction between the shape of a typical winter day such as Saturday 13/3/1999 and summer day such as Monday 16/8/1999. This is shown in figure 3.7. This difference is due to the high change in temperature values between the two days.

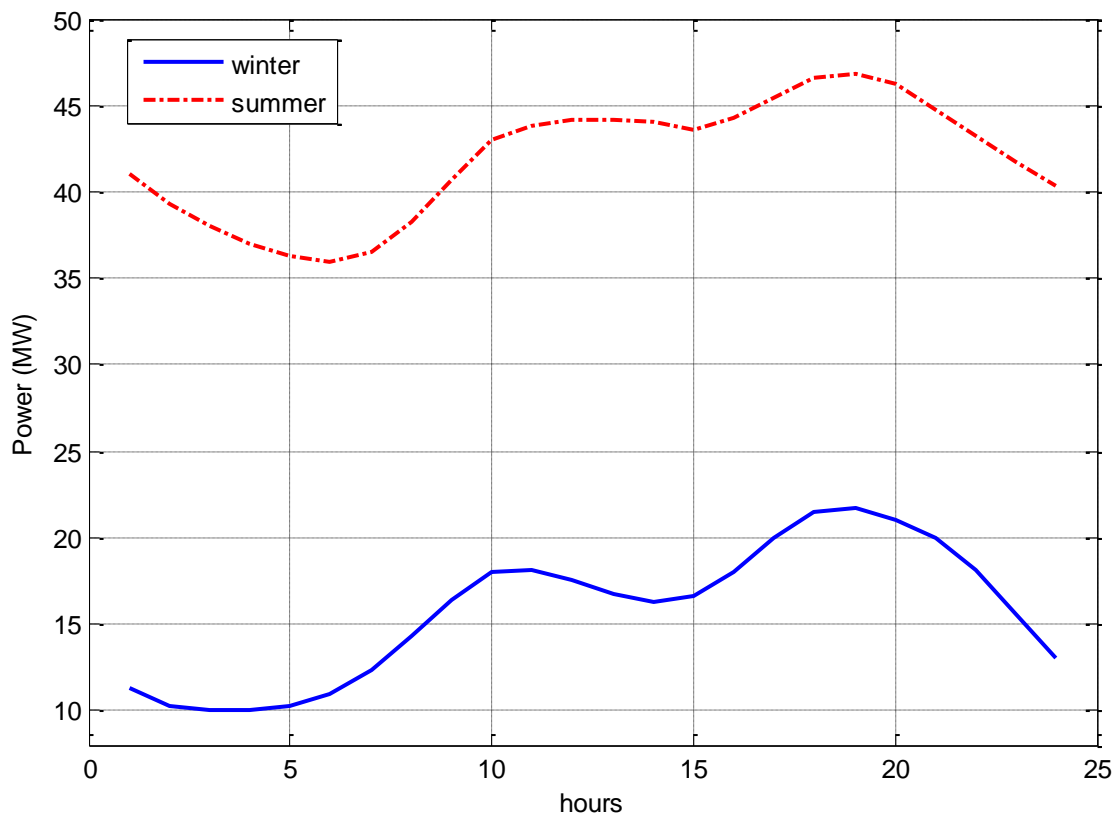


Figure 3.7: Typical winter and summer days, 1999

From the previous analysis, it is clear that there are different characteristics of days or group of days during the year that enforce the data to be separated to different modes with special characteristics. So, it is revealed that the entire year can be divided to different modes which are Ramadan mode, Eid Feter day mode, after Eid Feter days mode, Eid Hajj day mode, after Eid Hajj day mode, cold normal days mode, cold Thursdays mode, cold Fridays mode, hot normal days mode, hot Thursdays mode and hot Fridays mode. Also, some additional modes may be included like before eid Hajj days, mid-year vacation days, summer vacation and mid-term vacation. This will increase the accuracy of the results. Every mode has its own behavior which is different from other modes characteristics.

### 3.6.1.1 Ramadan mode ( r )

An interesting period is Ramadan month which is the month of fasting. In this Hijra month, people activities are totally different than any other Hijra months. For example, Ramadan is characterized by less working hours, no difference between week days and weekend days. Also, almost there is no difference between vacations and non-vacations, new dining hours, etc. Figure 3.8 shows power profile for sample days of Ramadan, 1999.

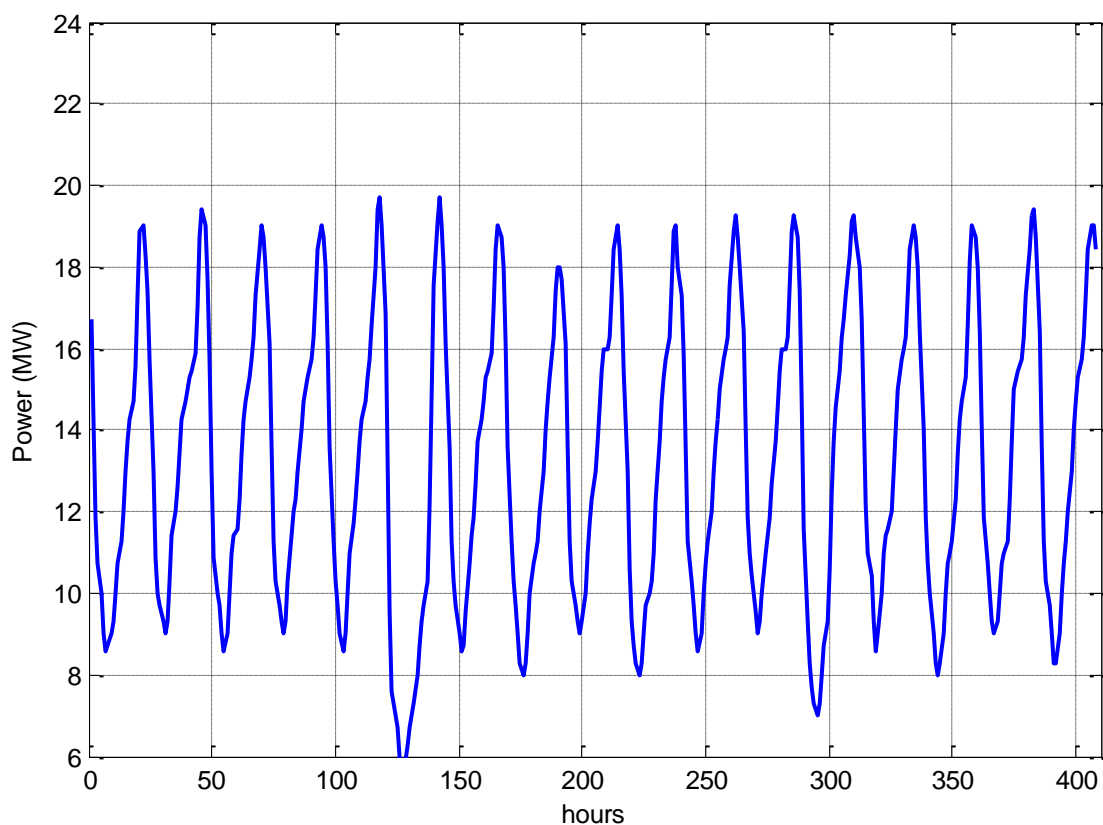


Figure 3.8: Typical Ramadan days, 1999

As shown, there is no clear distinction between weekends and weekdays, vacations and non-vacation days. This supports the decision to neglect the effect of week days and weekends characteristics in this period. Also, it is clear that Ramadan

month has its own characteristics which are totally different than other months. Because of fasting during day, there is no dip in the period of lunch time which is the case in other months.

A closer look at figure 3.8 concludes that also the peak hour in Ramadan is different than other months, which ranges normally between 7 PM to 8 PM. However, in Ramadan, it ranges between 9 PM to 11 PM as seen from figure 3.9.

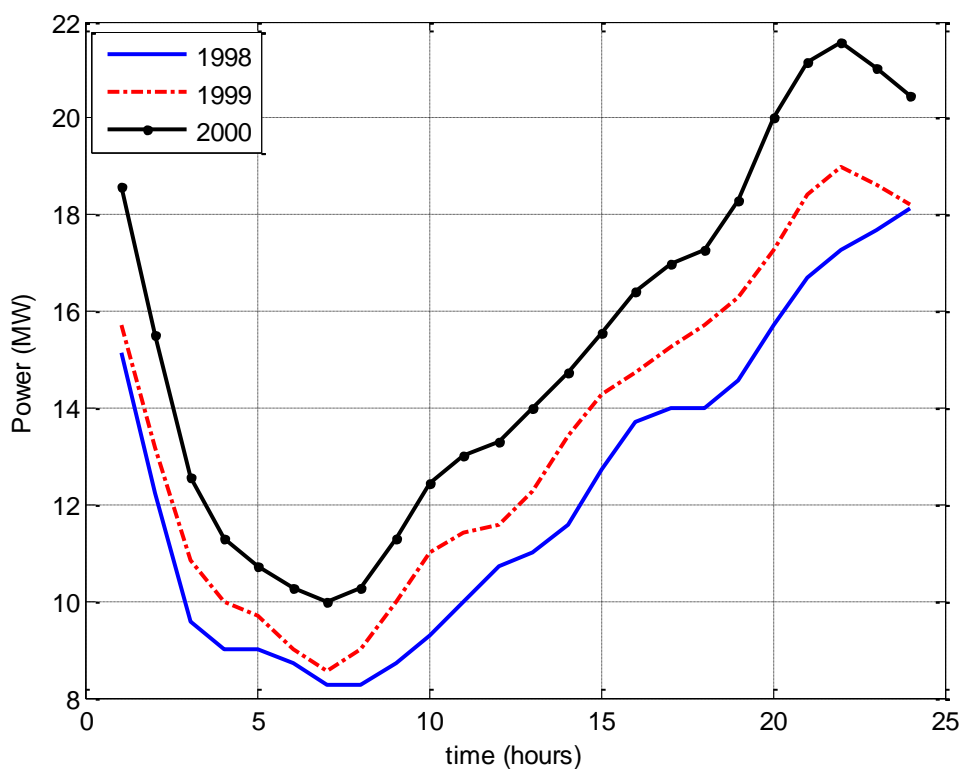


Figure 3.9: Typical Ramadan day, 1998, 1999 and 2000

### 3.6.1.2 Eid Feter day ( ef )

Eid Feter day has also special behavior. The load at this day is very low because people mostly in morning time stay outside their homes to perform Eid prayer and then meet with relatives, neighbors and friends. So, Eid Feter day, in addition to

Eid Hajj day, are mostly affected by people social habits. Figure 3.10 shows Eid Feter day for 1998, 1999 and 2000.

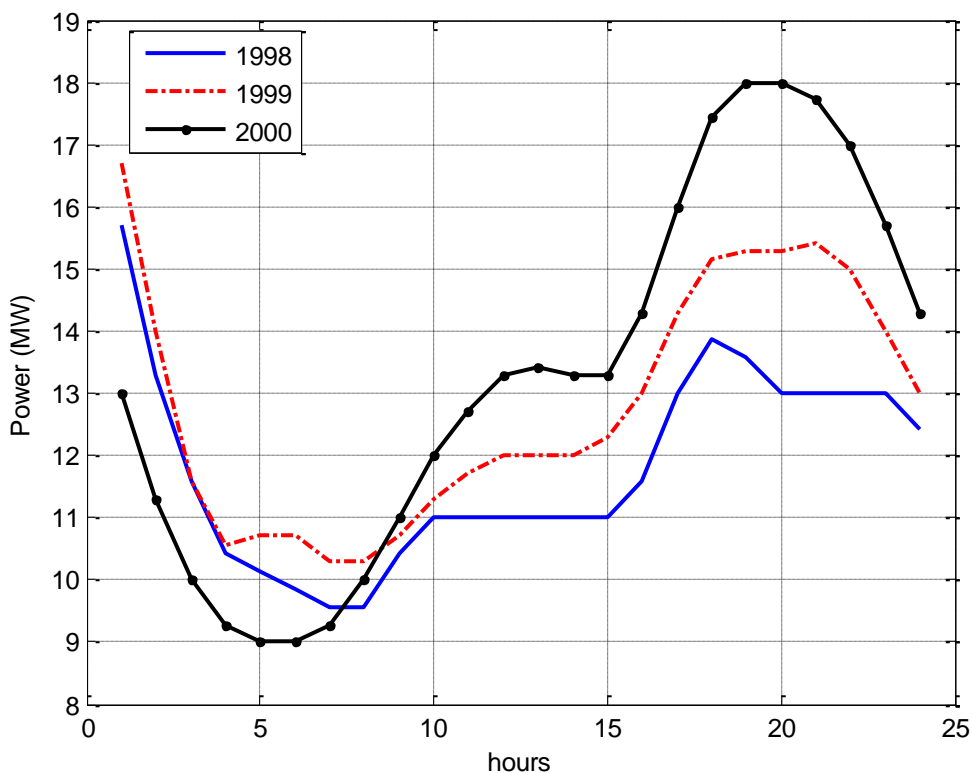


Figure 3.10: Eid Feter day, 1998, 1999 and 2000

Also, as seen previously from figure 3.5, the interval of Eid Feter day is clearly compared with previous and next modes for year 1999.

### 3.6.1.3 After Eid Feter days mode ( aef )

These days are the days coming directly after Eid Feter day period where a sharp decrease in the load curve is noticed in the Eid day load curve compared to the previous period. Then, the load increases gradually because of changeable people activities like preparing for schools and going back to normal dining hours which are totally different than those of Ramadan period. This gradual load rising continues until

the starting of the next mode which is cold normal days mode. This was also shown in figure 3.5 previously.

#### 3.6.1.4 Eid Hajj day mode ( eh )

As in Eid Feter day mode, a sharp decrease is clearly noticed in Eid Hajj day comparing to previous mode (cold days mode) and next mode (after Eid Hajj days mode). Figure 3.11 shows Eid Hajj day for 1999 and 2000.

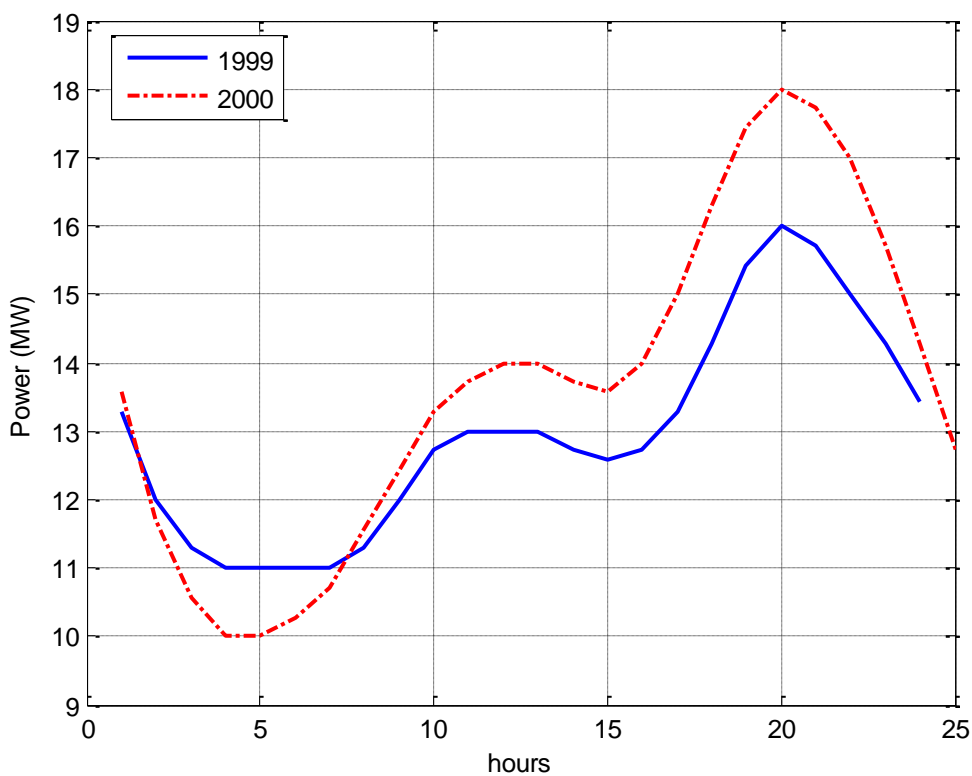


Figure 3.11: Eid Hajj day, 1999 and 2000



Also, figure 3.12 shows Eid Hajj day and its previous and next modes for 1999.

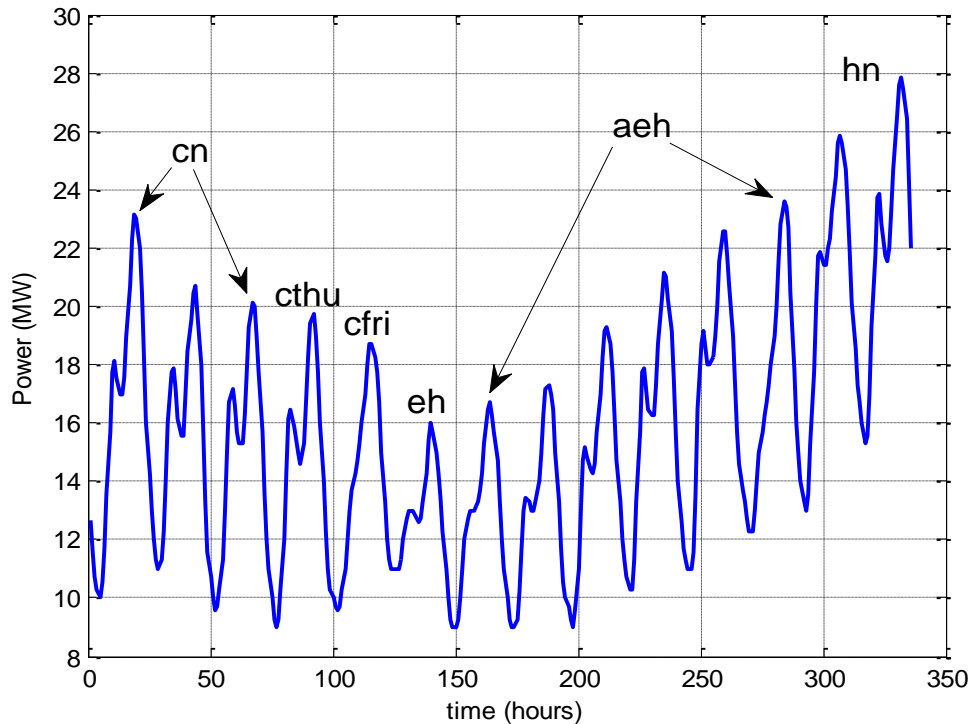


Figure 3.12: Eid Hajj day and its previous and next modes, 1999

### 3.6.1.5 After Eid Hajj days mode ( aeh )

As in after Eid day mode, the load curve is increasing gradually until the beginning of working days period as shown in figure 3.12.

### 3.6.1.6 Cold normal days mode ( cn )

This period is the period from Saturdays to Wednesdays which is the period of working days in KSA. As shown previously in figure 3.6, this figure shows the power demand for 1998, 1999 and 2000 for a typical week in February starting from Saturday to Friday. Similar behavior is noted for the five working days. The dip in the lunch time is also noticed clearly. Moreover, there is a fall in the load curve in the weekend days compared to the week days of this interval. So, it can be noted that electrical load in weekend (Thursday and Friday) is usually lower than of working days (Saturday to

Wednesday). This is due to the economical and social activities on working days are at higher level than on the weekend days.

### 3.6.1.7 Cold Thursdays mode ( cthu )

The official weekend days in KSA are Thursdays and Fridays. Each day has its own characteristics. Thursday is clearly different than other days of the week and hence it will be classified as a mode. Figure 3.13 shows the load curve for typical Thursdays selected in winter season in the three years.

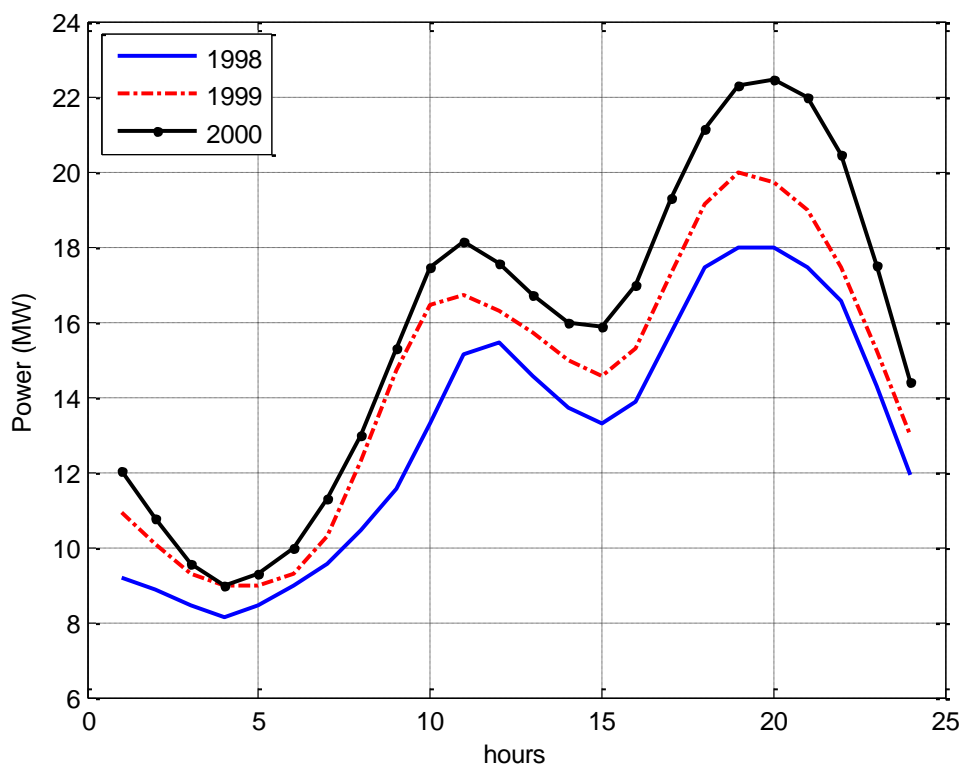


Figure 3.13: Typical Thursdays, cold region, 1998, 1999 and 2000

### 3.6.1.8 Cold Fridays mode ( cfri )

In cold Friday mode, Juma'a prayer is an important activity of people that has a main impact on load curve behavior in Fridays. Figure 3.14 shows the load curve for typical Fridays selected from winter season for all the three years.

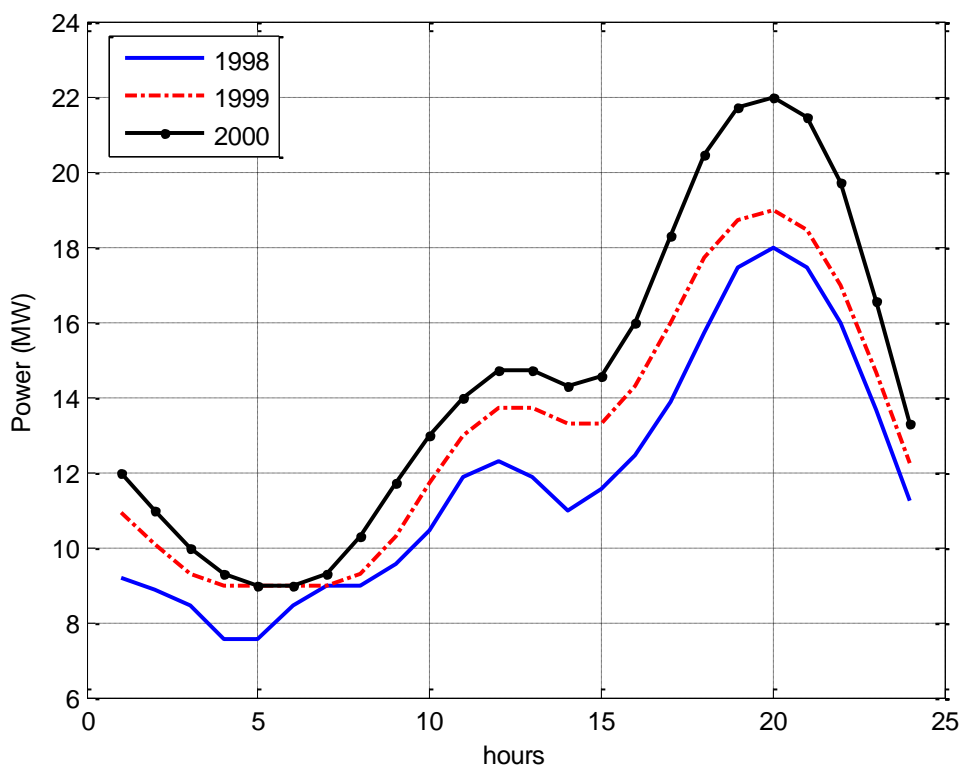


Figure 3.14: Typical Fridays, cold region, 1998, 1999 and 2000

### 3.6.1.9 Hot normal days mode ( hn )

This period is the period of high temperature values during working and schools intervals. It is the most affected period by temperature and humidity conditions where high load values are reached during this period. As done in cold period, the hot normal days will be classified as a mode. Figure 3.15 shows the power demand for

1998, 1999 and 2000 for a typical week in hot period starting from Saturday to Friday.

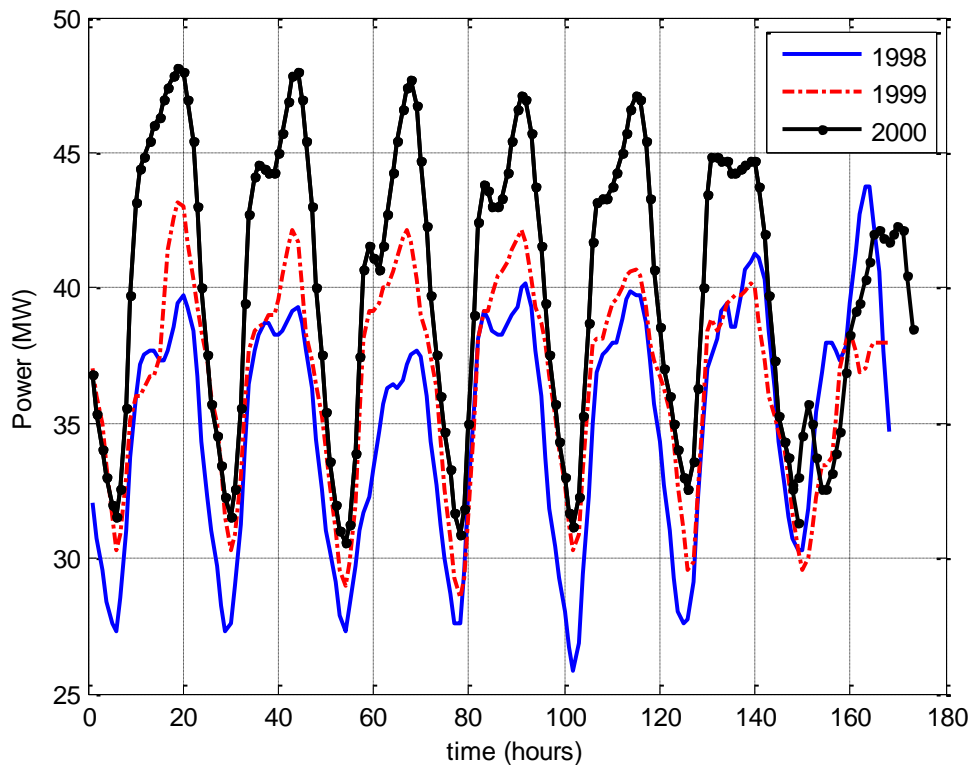


Figure 3.15: Typical hot region week, 1998, 1999 and 2000

#### 3.6.1.10 Hot Thursdays mode ( hthu )

As in cold period, Thursday is a vacation day and people activities differ from working and schools days. In hot Thursday mode, the shape of the load curve is also different than weekdays as shown in figure 3.15. Also, figure 3.16 shows a typical Thursday in hot period for the three years 1998, 1999 and 2000.

#### 3.6.1.11 Hot Fridays mode ( hfri )

Finally, Friday in hot region has also its own characteristics as shown in figure 3.15.

Figure 3.17 shows a typical Friday in hot period for the three years 1998, 1999 and 2000.

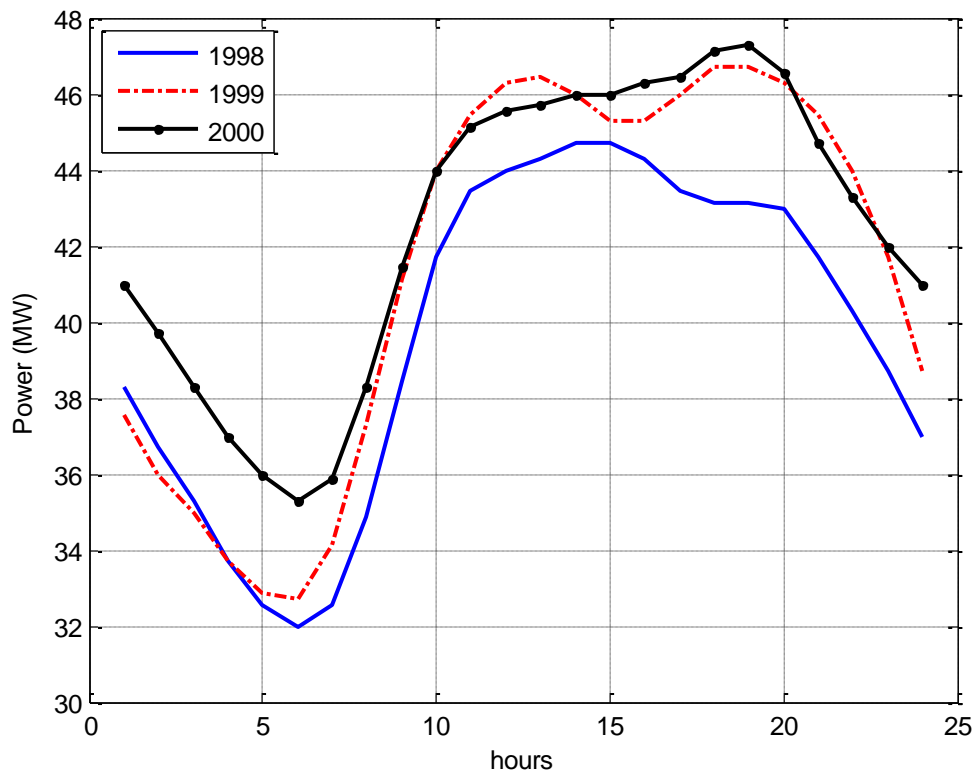


Figure 3.16: Typical Thursdays, hot region, 1998, 1999 and 2000

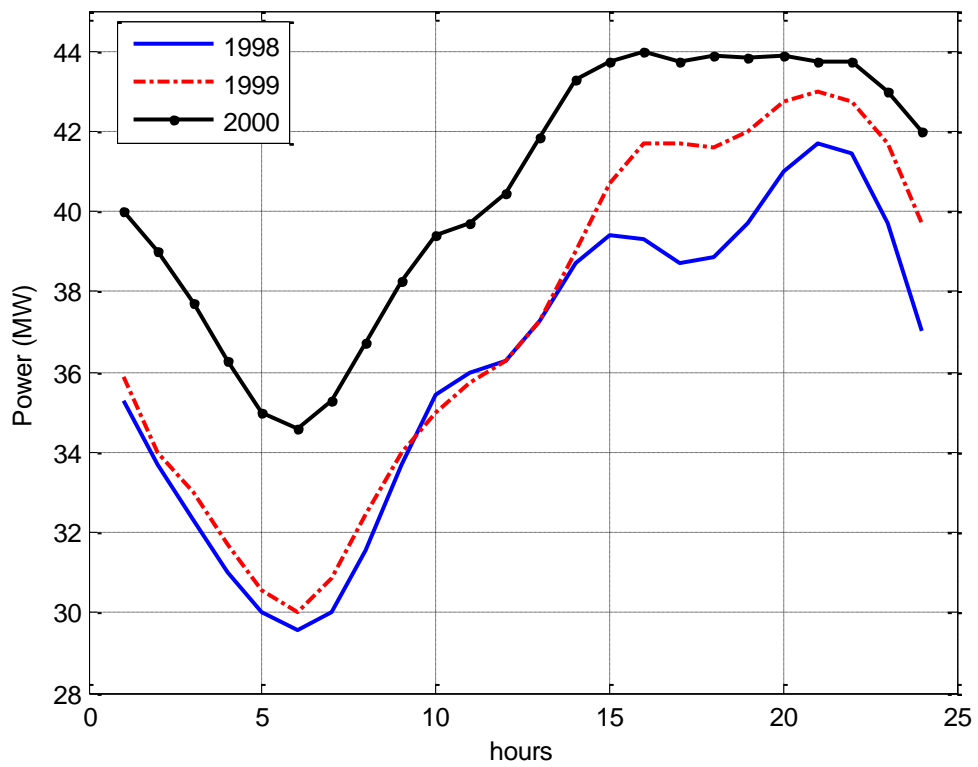


Figure 3.17: Typical Fridays, hot region, 1998, 1999 and 2000

In addition, summer vacation could be classified as a separate mode or it may be included in hot period modes. Its behavior is almost similar to the hot period modes.

### **3.6.2 Marafiq Data**

This residential area data is provided by Marafiq Company in Yanbu industrial city in KSA. The available data is from 1 January 2009 to 10 December 2011. For training and model building, 2009 and 2010 will be used to forecast the load of 2011. The data is for a residential area in Yanbu industrial city characterized by almost same weather conditions and social activities of Eastern Province. The difference is in the nature of people activities before and after vacations. This city is almost evacuated at official companies and schools vacation periods. In addition to schools periods, working companies' days affect the load significantly where some companies' employees stay at the city in time of short schools vacations like mid-term or mid-year vacations. Therefore, due to this similarity, modes classification will be almost similar to that in SEC data except for some modes such as mid-term and mid-year vacations modes. For this residential area at 2009, the hourly load and temperature profiles and the daily peak load and temperature values displayed in figure 3.18, show clearly that load consumption is affected by the temperature throughout the year.

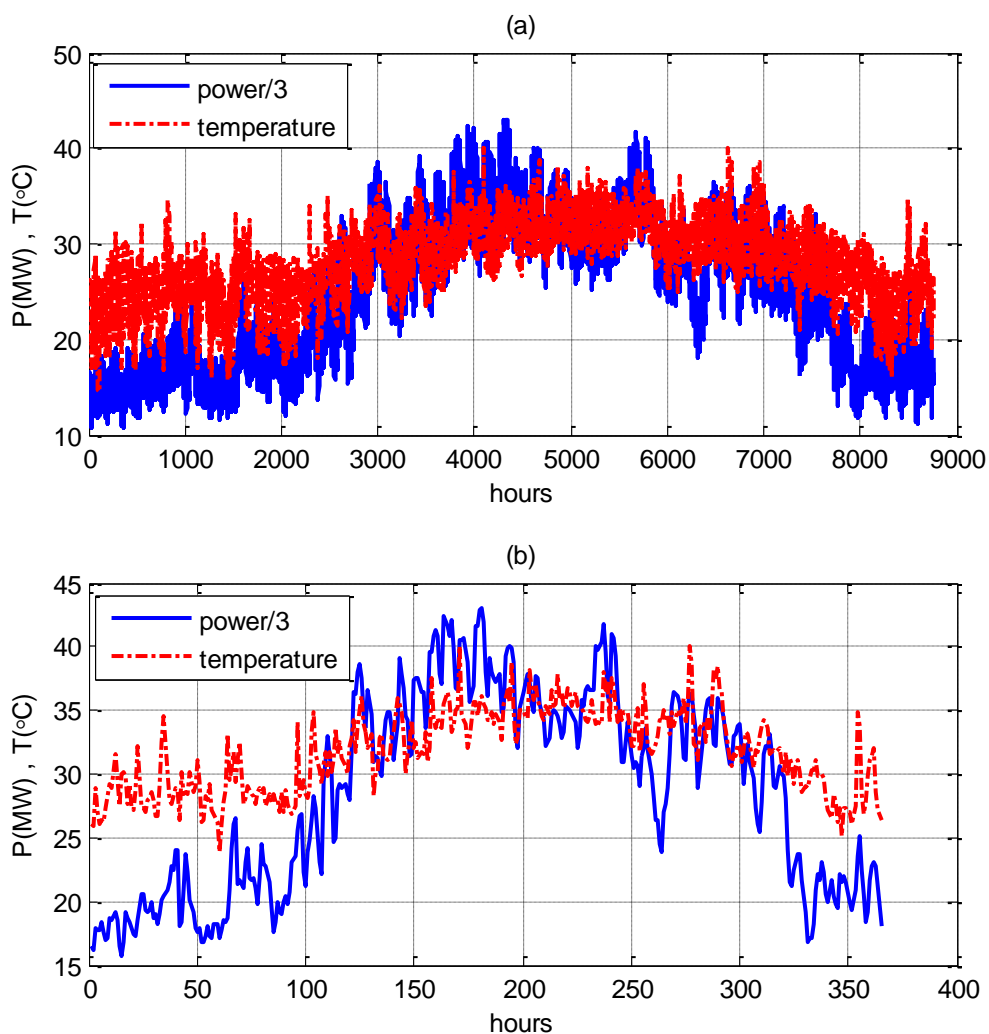


Figure 3.18: (a) Power and temperature profiles for Marafiq data, 2009  
 (b) Daily peak demands and temperatures for Marafiq data, 2009

By looking to the load consumption curve for Ramadan 2009 as shown in figure 3.19, it is clear that the load curve is following the temperature curve and it drops sharply at the last day of working days of the companies which is Wednesday 26<sup>th</sup> of Ramadan. This is because at these days, official holidays for companies start and people leave the city. Consequently, the residential load drops.

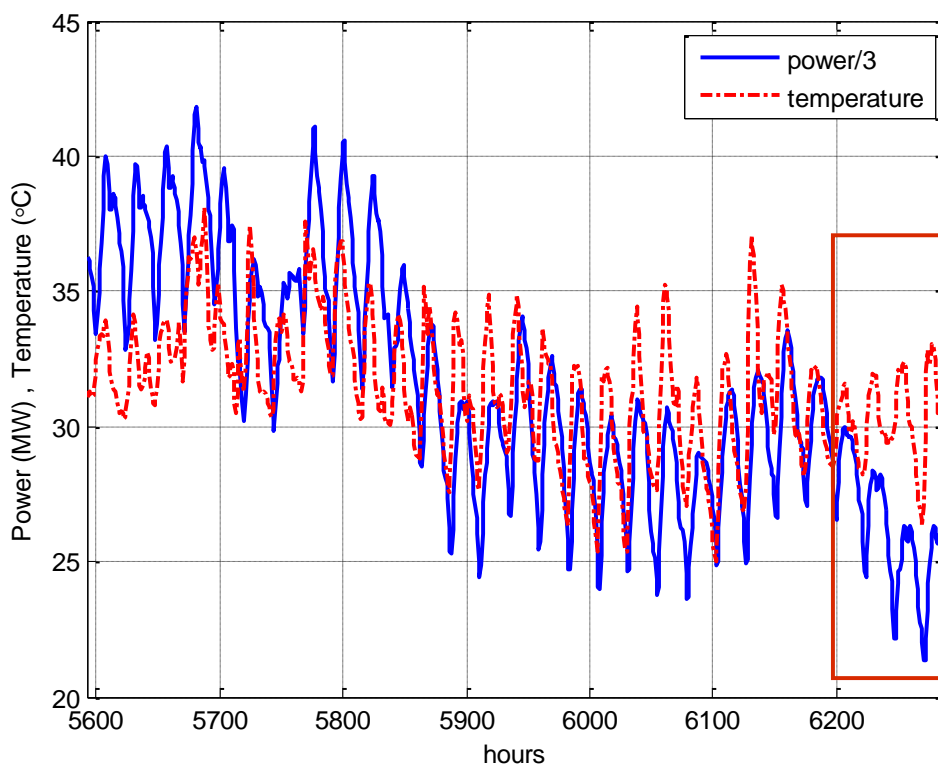


Figure 3.19: Power and temperature profiles, Marafiq data, Ramadan, 2009

So, companies' holiday may be classified as a separate mode but since its shape is almost as other Ramadan days, it will be included in Ramadan mode and the shifting up or down will be analyzed when dealing with average daily power forecasting. Also, week days and weekends could be categorized as separate modes. So, Ramadan week days, Ramadan Thursday, and Ramadan Friday modes are present. Especially in Ramadan, considering week days and weekends as separate modes does not affect the results considerably since there is no much difference between week days and weekends load curve behavior and hence they may be included as Ramadan mode. It is only considered for better results.

In addition, mid-year vacation for Yanbu industrial city is mainly affected by holidays of companies and as seen from figure 3.20, there is no clear distinction



between mid-year vacation and other cold normal days and hence it may be counted as normal cold days. Also, the impact of temperature is clearly noted.

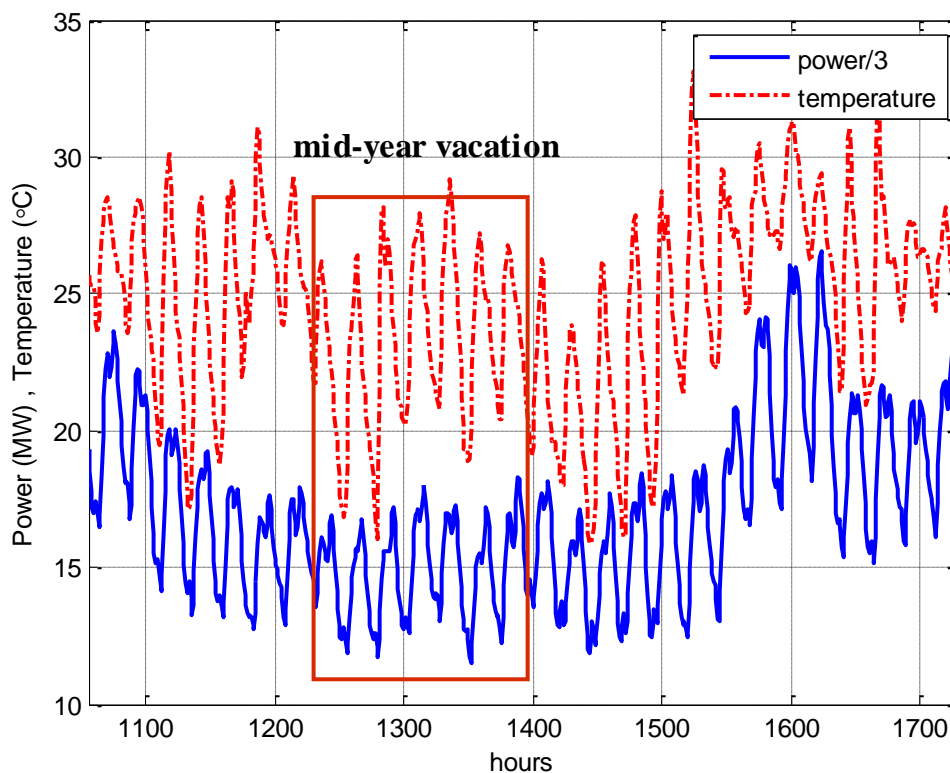


Figure 3.20: Power and temperature profiles, Marafiq data, 14/2-13/3/2009

Therefore, in summary, same modes used in SEC data will be used here. Also, some new modes will be added. These modes include Ramadan mode, Eid Feter day mode, after Eid Feter days mode, Eid Hajj day mode, after Eid Hajj day mode, cold normal days mode, cold Thursdays mode, cold Fridays mode, hot normal days mode, hot Thursdays mode and hot Fridays mode, summer period mode, mid-year and mid-term vacations modes.

### 3.6.3 USA Data

The data consists of measured hourly load and temperature data for the Puget power utility, Seattle, USA, over the period 1 January 1985 to 31 December 1990. The nature of people activities and weather variables are completely different from that of SEC and Marafiq data. So, different modes categorization will be considered in this type of data.

Unlike KSA, the working days for USA are from Mondays to Fridays while weekend days are Saturdays and Sundays. Also, some holidays and special days are present in USA and not present in KSA like New Year's Day, Labor Day, Thanksgiving Day and Christmas day.

Regarding weather conditions, the seasonally change from winter to spring to fall to summer is noted clearly in USA, whereas in KSA, only summer and winter load curve behavior is present. So, in addition to special days modes, the modes could be classified to winter, spring, fall and summer shapes intervals. With the impact of weather conditions and seasons change, the daily load curve also changes.

As in KSA, the effect of week days and weekend days is very significant; every interval will have week days mode (from Mondays to Fridays), Saturday mode and Sunday mode. Figure 3.21 shows typical weeks starting from Monday to Sunday for each season. Therefore, as expected, week days in every season are different in behavior and higher in consumption than weekend days. In special days analysis, there are special activities for people to do at these days. For example, in Thanksgiving Day, human behavior is completely different from any other normal day. So, every special day will be separated as a mode.

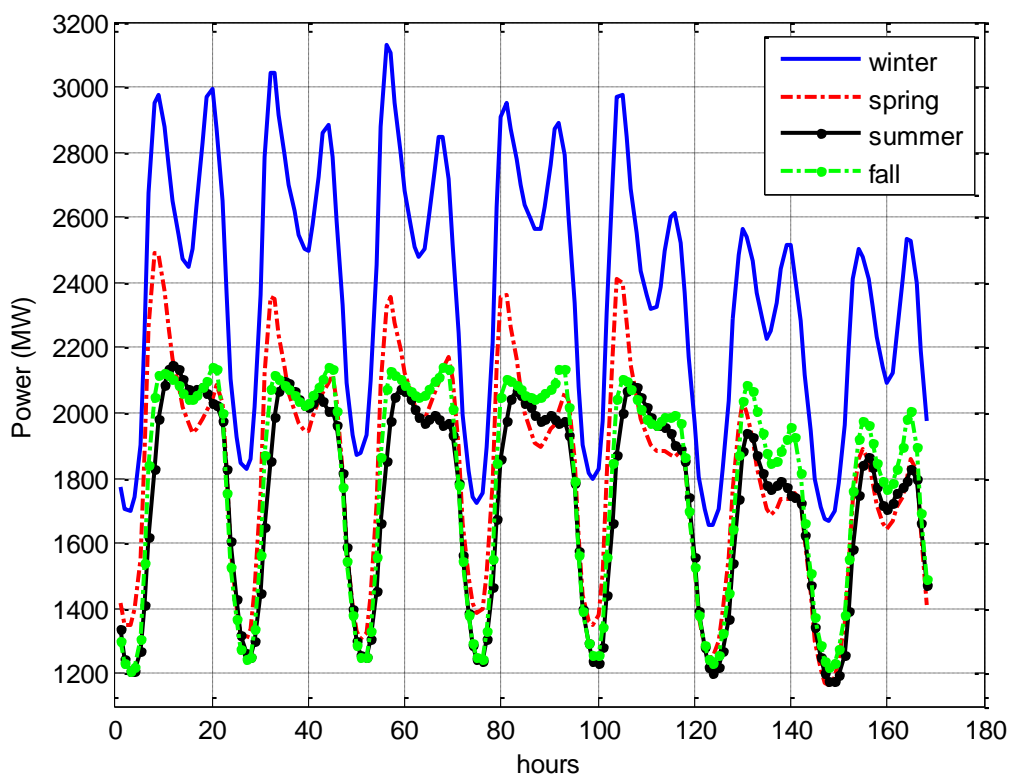


Figure 3.21: Load profile for sample week from each season, Seattle, USA, 1989

All special days dates in USA were found from reference [42]. However, some of them are not official and cannot be identified to be special days or not. So, there is a problem of how to specify whether these days are special or not, or whether they have special characteristics that make the load curve to be unique. The solution to this is simply by plotting these days, and if any day seems to have special behavior, it will be clear and classified as a separate mode. If not, it will be considered as a normal day and will be classified within its previous days' mode. Figure 3.22 show load profiles of some special days in Seattle, USA, 1989. For example, Columbus Day will be considered as a normal day since it does not have special characteristics that are different from its previous and next days. However, Thanksgiving Day has a unique and special behavior which is different from its previous and next days that support the

decision to separate it as a mode. So, same approach is applied to all official and Federal days.

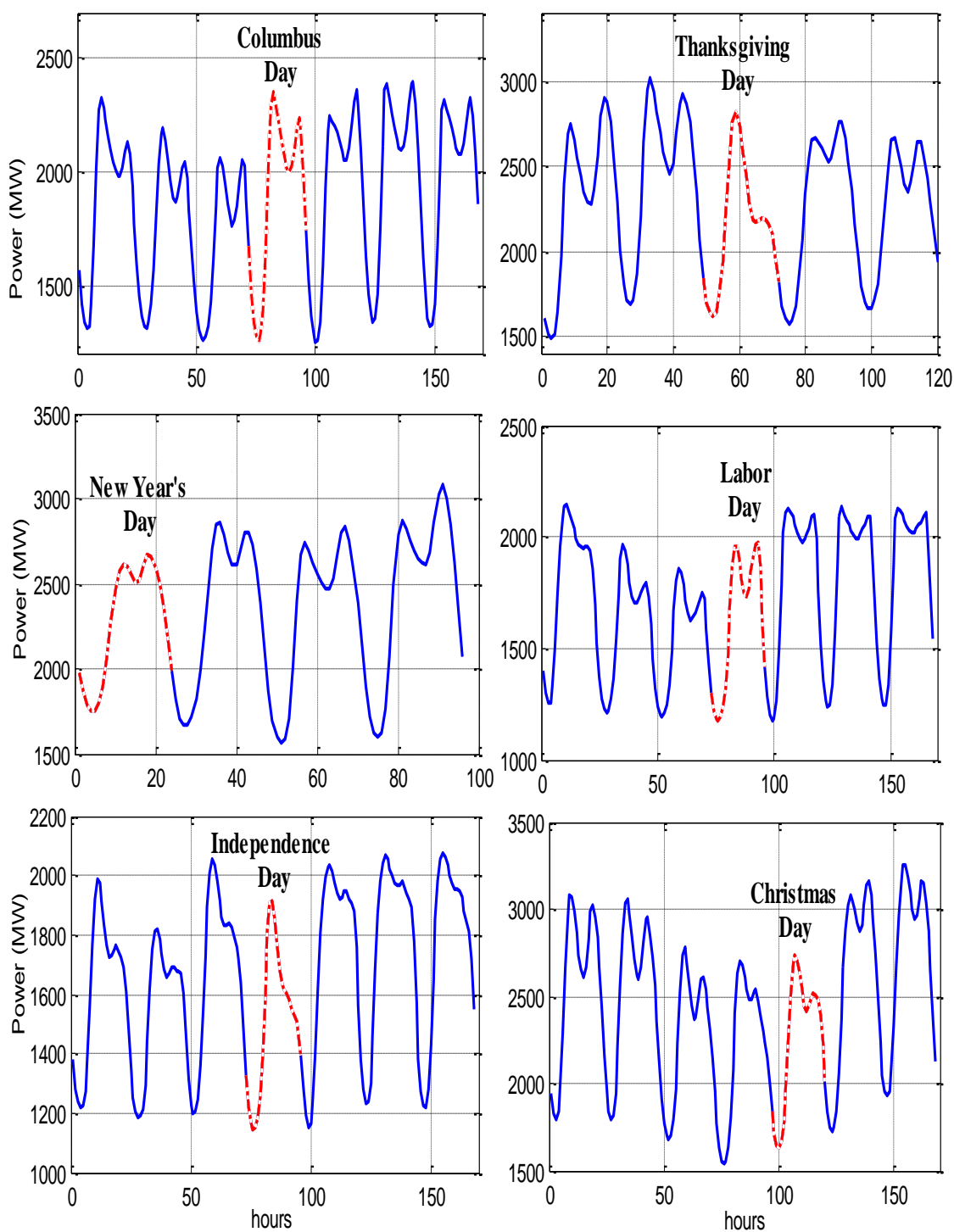


Figure 3.22: Power profile for some special days in Seattle, USA, 1989

### **3.7 Summary and Conclusions of the Chapter**

The following points have been addressed in this chapter:

- The main calendar in KSA is the Hijra calendar while the collected data are for Gregorian calendar. So, adjustments and transferring have been done between the two calendars.
- The official working days for KSA are from Saturdays to Wednesdays whereas the weekend days are Thursdays and Fridays.
- The official working days for USA are from Mondays to Fridays while the weekend days are Saturdays and Sundays.
- The data is filtered, arranged and validated for the proposed model.
- The affecting variables on load consumption have been identified to be weather conditions and people activities.
- In terms of people activities and load shape affected by weather variables, the data for one year for each data source is divided into modes describing their behaviors.
- Every mode has day or group of days that have similar characteristics.
- Some submodes could be accommodated in the corresponding main mode and some others cannot, and have to be considered as separate modes.
- Moreover, the days belonging to one mode in one year are similar in shape to the days in the same mode in other years. The difference is only shifting up or down because of the growth rate.
- So, now, all parameters, modes, and weather variables are ready to be analyzed to find the best model. This will be discussed next chapter.

## **CHAPTER 4**

### **ANALYSIS OF THE APPROACHES USED**

In this study, two approaches will be used in STLF. The first method is Artificial Neural Network model analysis (ANN) while the second one is the hybrid analytical model. This chapter presents the concept and analysis of both methods.

#### **4.1 NN Model**

##### **4.1.1 Overview**

NNs are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A NN can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly NNs are adjusted, or trained, so that a particular input

leads to a specific target output. Such a situation is shown in figure 4.1. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target.

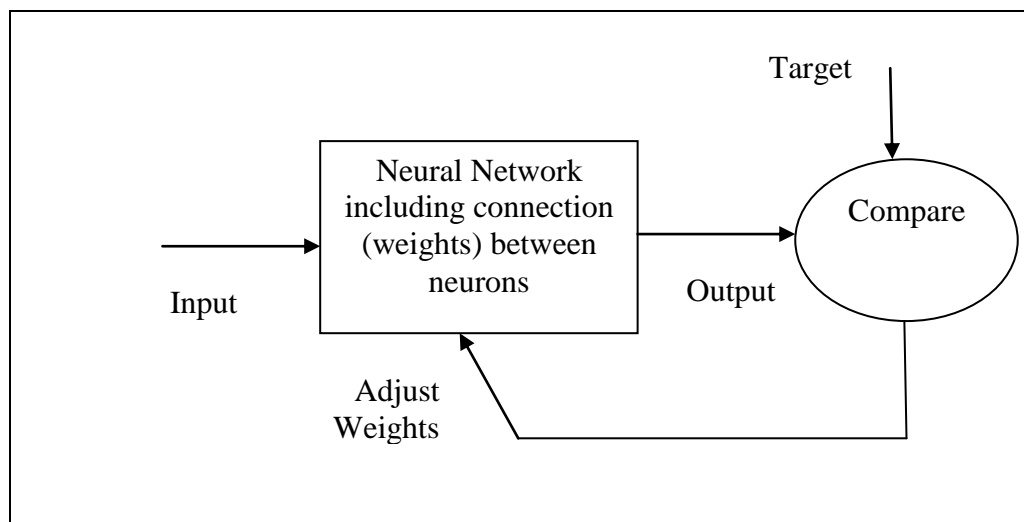


Figure 4.1: Concept of NN

NNs have been trained to perform complex functions in various fields of applications including pattern recognition, identification, classification, speech, vision and control systems. [43]

#### 4.1.2 NNs Applications

ANNs have wide area of applications. For example, they are used in business works, aerospace, automotive, banking, credit card activity checking, entertainment, defense, industrial, electronics, financial, manufacturing, insurance, oil and gas exploration, telecommunications, speech, robotics, medical, securities and transportation applications. [43]

The application of NNs in different power system operation and control strategies has led to acceptable results. NNs can be applied to the fields of load forecasting, fault diagnosis/fault location, economic load dispatch, optimization and

loss reduction. Moreover, NNs are used in security assessment and enhancement, frequency control, transient stability, voltage and reactive power control. [45]

### 4.1.3 Neuron Model

A neuron with a single scalar input and no bias appears on figure 4.2a. The scalar input  $p$  is transmitted through a connection that multiplies its strength by the scalar weight  $w$  to form the product  $wp$ , again a scalar. Here the weighted input  $wp$  is the only argument of the transfer function  $f$ , which produces the scalar output  $a$ . The neuron on the figure 4.2b has a scalar bias,  $b$ . one can view the bias as simply being added to the product  $wp$  as shown by the summing junction or as shifting the function  $f$  to the left by an amount  $b$ .

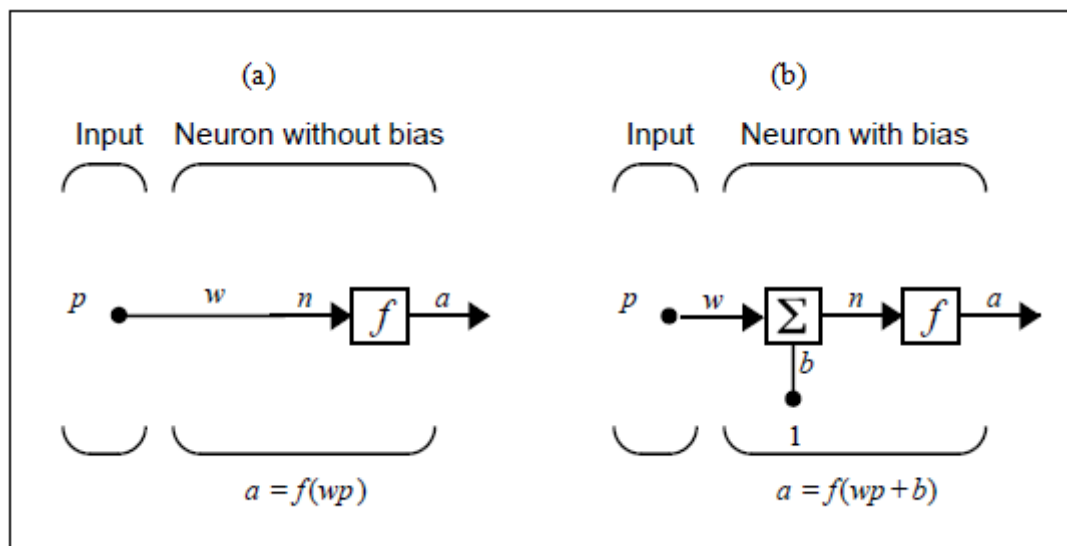


Figure 4.2: (a) Neuron with a single scalar input and no bias  
(b) Neuron with a scalar bias

The bias is much like a weight, except that it has a constant input of 1. The transfer function net input  $n$ , again a scalar, is the sum of the weighted input  $wp$  and



the bias  $b$ . This sum is the argument of the transfer function  $f$ . Here  $f$  is a transfer function, typically a step function or a sigmoid function, that takes the argument  $n$  and produces the output  $a$ . It is important to note that  $w$  and  $b$  are both adjustable scalar parameters of the neuron. The central idea of NNs is that such parameters can be adjusted so that the network exhibits some desired or interesting behavior. Thus, the network can be trained to do a particular job by adjusting the weight or bias parameters, or the network itself will adjust these parameters to achieve some desired end. Many transfer functions are used in NNs analysis. The most commonly used functions are hard-limit, linear and log-sigmoid transfer functions. [43]

#### 4.1.4 Network Architectures

Two or more of the neurons shown earlier can be combined in a layer, and a particular network could contain one or more such layers.

##### 4.1.4.1 A Layer of Neurons

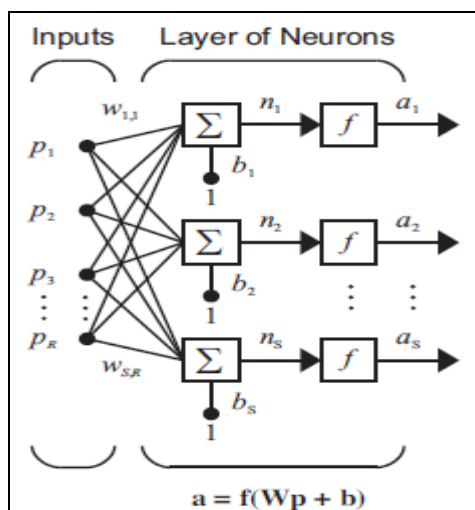


Figure 4.3: One-layer network

A one-layer network with  $R$  input elements and  $S$  neurons is shown in figure 4.3. In this network, each element of the input vector  $p$  is connected to each neuron

input through the weight matrix  $W$ . The  $i^{\text{th}}$  neuron has a summer that gathers its weighted inputs and bias to form its own scalar output  $n(i)$ . The various  $n(i)$  taken together form an  $S$  element net input vector  $\mathbf{n}$ . Finally, the neuron layer outputs form a column vector  $\mathbf{a}$ . The expression for  $\mathbf{a}$  is shown at the bottom of the figure. It is common for the number of inputs to a layer to be different from the number of neurons (i.e.,  $R$  is not necessarily equal to  $S$ ). A layer is not constrained to have the number of its inputs equal to the number of its neurons. The input vector elements enter the network through the weight matrix  $W$ .

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,R} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,R} \\ w_{S,1} & w_{S,2} & \cdots & w_{S,R} \end{bmatrix}$$

The row indices on the elements of matrix  $W$  indicate the destination neuron of the weight, and the column indices indicate which source is the input for that weight. Thus, the indices in  $w_{1,2}$  say that the strength of the signal from the second input element to the first (and only) neuron is  $w_{1,2}$ . Figure 4.4 shows one layer network with  $R$  input elements and  $S$  neurons.

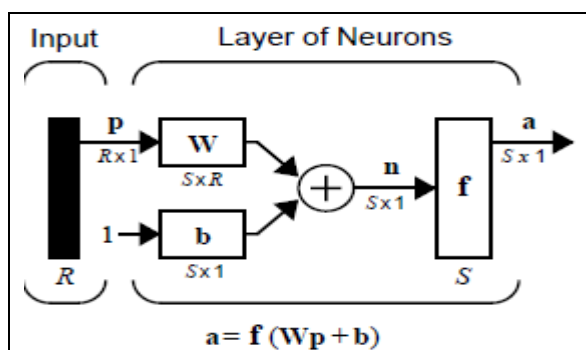


Figure 4.4: One-layer network with  $R$  input elements and  $S$  neurons

Here  $p$  is an  $R$  length input vector,  $W$  is an  $S \times R$  matrix, and  $a$  and  $b$  are  $S$  length vectors. As defined previously, the neuron layer includes the weight matrix, the multiplication operations, the bias vector  $b$ , the summer, and the transfer function boxes. [43]

#### 4.1.4.2 Multiple Layers of Neurons

A network can have several layers. Each layer has a weight matrix  $W$ , a bias vector  $b$ , and an output vector  $a$ . To distinguish between the weight matrices, output vectors, etc., for each of these layers in figures 4.5, the number of the layer is appended as a superscript to the variable of interest.

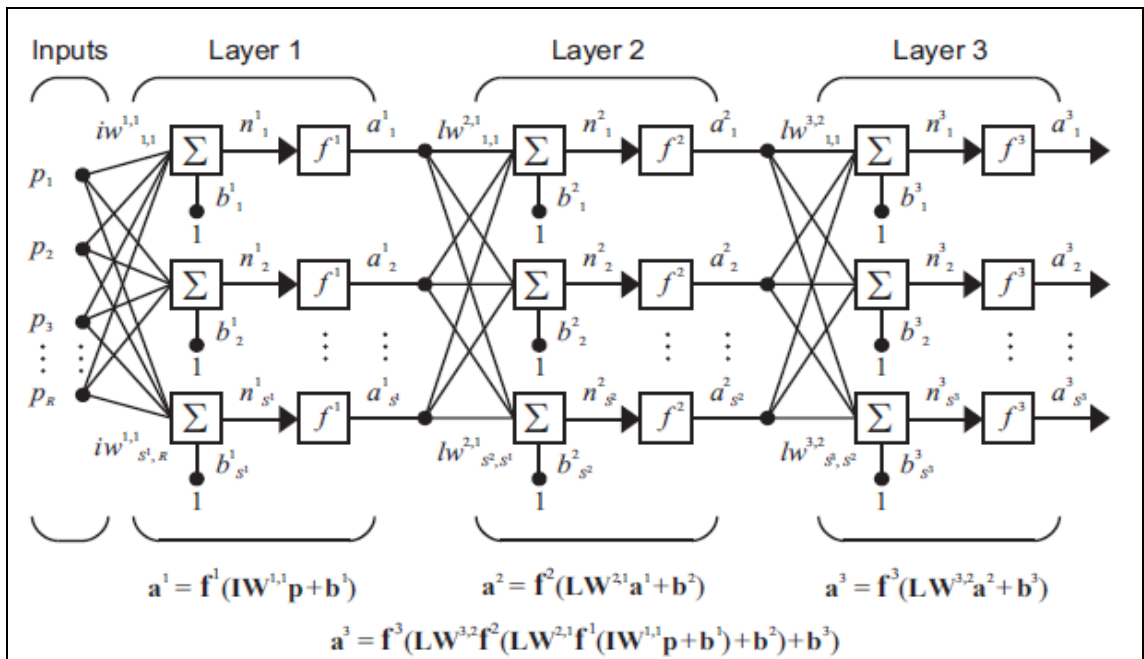


Figure 4.5: Multiple Layers of Neurons

The network shown in figure 4.5 has  $R_1$  inputs,  $S_1$  neurons in the first layer,  $S_2$  neurons in the second layer, etc. It is common for different layers to have different numbers of neurons. A constant input 1 is fed to the bias for each neuron. The outputs of each intermediate layer are the inputs to the following layer. Thus layer 2

can be analyzed as a one-layer network with  $S_1$  inputs,  $S_2$  neurons, and an  $S_2 \times S_1$  weight matrix  $W_2$ . The input to layer 2 is  $\mathbf{a}_1$ ; the output is  $\mathbf{a}_2$ . Now that all the vectors and matrices of layer 2 have been identified, it can be treated as a single-layer network on its own. This approach can be taken with any layer of the network. The layers of a multilayer network play different roles. A layer that produces the network output is called an output layer. All other layers are called hidden layers. The three-layer network shown earlier has one output layer (layer 3) and two hidden layers (layer 1 and layer 2). [43]

#### **4.1.5 Proposed NN Model**

The model is implemented on two applications; next hour and next day load forecasting. These tests are applied on all sources of data mentioned previously in chapter 3, SEC data for KSA Eastern Province, Marafiq data for Yanbu industrial city and Seattle data, USA. The design of the model, process, and approach are explained in this section.

According to the nature of each set of data, number of layers and hidden neurons are selected. Many previous works try to optimize the selection of these parameters values. However, there is no rule to decide these values. This is highly dependent on the application, nature of data and number of samples used. Normally, trial and error method is followed to specify the values of these parameters.

In this work, the model is a feed-forward ANN with tan-sigmoid transfer functions in the hidden layers and linear function in the output layer. Number of layers and hidden neurons is different for each data. By trial and error, the assigned values for each set of data for next hour and day load forecasting models are shown in table 4.1.

Table 4.1: Summary of parameters selected in the proposed models

	Next Hour Model		Next Day Model	
	number of hidden layers	number of hidden neurons for each layer	number of hidden layers	number of hidden neurons for each layer
SEC Data	1	3	2	10 , 5
Marafiq Data	1	5	2	14 , 2
USA Data	1	2	3	6 , 8 , 4

#### 4.1.5.1 Input Vector Configuration

For next hour load forecasting for all data sources, the input vector to the ANN includes hour, day sequence through the year, mode number, temperature and humidity (except for USA, where humidity data is not available), all of these inputs are for the forecasted hour. Also, previous hours load historical data include all previous 24 hours load consumption including the previous hour to the forecasted one. Table 4.2 depicts the details of the input vector and model structure for next hour load forecasting.

Table 4.2: Input configuration for next hour load forecasting

Inputs						Output
P(h-1),P(h-2)..... .....P(h-24)	h	dy(h)	m(h)	T(h)	H(h)	P(h)
Previous 24 hours loads to the forecasted hour	Forecasted hour	Day sequence through the year of the day of the forecasted hour	Mode number of the day of the forecasted hour	Expected temperature of the forecasted hour	Expected humidity of the forecasted hour	Load of next hour

Two approaches for training and testing are followed, namely, static and dynamic approaches. In the static approach, the number of training epochs is constant. The training is stopped at the hour 24 of the last day of the last trained year (2004 for SEC, 2010 for Marafiq and 1989 for Seattle). To forecast any hour from the evaluating year, the model is not re-built. However, in dynamic approach, the training is always updated and stopped at the previous hour to the forecasted one. So, to forecast any hour from the forecasted year, the model has to be updated to include all previous data to the forecasted hour. For example, to forecast the hour 9 from 5 August, 2011 from Marafiq data, the training is stopped at the hour 24 from 31 December, 2010 in static method and the corresponding number of epochs is 17352. However, the training is stopped at the hour 8 from 5 August, 2011 using dynamic approach with 22544 epochs number. In this work, dynamic approach is followed to utilize the most up to date weather conditions and load behavior of the forecasted hour. This example is shown in table 4.3.

Table 4.3: Input parameters values to forecast hour 9 of 5 August, 2011

Inputs						Next Hour Load Forecasting Trained Static & Dynamic Neural Networks Model	Output
P(h-1),P(h-2),.....P(h-24)	h	dy(h)	m(h)	T(h)	H(h)		P(h)
92.38,91.18,96.76,101.89 104.8,107.23,107.75,110.83 111.65,114.56,114.52,114.46 114.19,109.18,111.72,112.85 114.24,113.23,110.59,107.46 107.02,104.49,98.86,95.3	9	5	6.7	32.7	94.82		Pactual(h)= 94.67 MW Pforecasted(h)= 95.12 MW

For next day load forecasting, the input vector to the ANN includes following parameters related to the forecasted hour,  $h$  of day,  $d$ :

- Hour from 1 to 24
- Temperature of the forecasted hour
- Humidity of the forecasted hour
- Mode number
- Day sequence through the year from 1 to 365

The historical load data selected for the input vector of the next day load forecasting model are the load, temperature and humidity values at the same hour of the previous day, previous two days, previous three days and previous week.

This is shown in table 4.4.

Table 4.4: Input configuration for next day load forecasting

Inputs						Output
P(d,h-24),P(d,h-48), P(d,h-72),P(d,h-168)	h	dy(h,d)	m(h,d)	T(h,d)	H(h,d)	P(h,d)
T(d,h-24),T(d,h-48), T(d,h-72),T(d,h-168)						
H(d,h-24),H(d,h-48), H(d,h-72),H(d,h-168)						
Previous 24,48,72 and 168 hours loads, temperatures and humidity to the forecasted hour of next day, d	Forecasted hour of next day d	Day sequence through the year of next day	Mode number of next day	Expected temperature of the forecasted hour in next day	Expected humidity of the forecasted hour in next day	Load for hour h of next day d

As in next hour model, same static and dynamic approaches will be followed in next day model. In static model, the training is always stopped at the last day of the last training year whereas in dynamic approach, it includes all previous days to the forecasted day and the training is stopped at the previous day to the forecasted one.

#### 4.1.5.2 Data Preprocessing

Before training, it is useful for all the inputs and targets to be scaled so that they always fall within a specified range. Equation 4.1 is used for each input and target independently.

$$y_s = \frac{(y_{\max} - y_{\min})(x - x_{\min})}{x_{\max} - x_{\min}} + y_{\min} \quad (4.1)$$

where  $y_s$  is the scaled data element,  $x$  is the original data element for each input and target vectors,  $x_{\max}$  and  $x_{\min}$  are the maximum and minimum corresponding data element respectively. Due to nature of the sigmoid function, the outputs of the neurons fall in the interval of -1 and +1. Therefore,  $y_{\max}$  and  $y_{\min}$  are set to 1 and -1, respectively. [46]

## 4.2 Hybrid Analytical Model

As mentioned in Chapter 3, the yearly load consumption is divided to modes. Every mode has day or group of days characterized by special daily load behavior shape. Also, the parameters affecting the consumption are attributed to weather conditions and people activities. So, the formulation and building of the final analytical model will be analyzed extensively. Moreover, modes analysis (ac components) and average power (dc component) will be analyzed separately and then their impacts will be combined to reach to the proposed forecasting model. In modes



analysis, Fourier Transform concept will be applied, while ANN will be used to forecast next day average load. Since this ANN and Fourier Transform analysis are used in this method, it is called hybrid analytical model. So, initially, an overview about Fourier Transform will be shown. Next, the above mentioned modes and weather variables will be studied. Carrier function, which is considered as the average daily power or the dc component, will be processed by ANN.

#### 4.2.1 Fourier Transform Concept

The Fourier Transform, in essence, decomposes or separates a waveform or function into sinusoids of different frequency which sum to the original waveform. It identifies or distinguishes the different frequency sinusoids and their respective amplitudes. The Fourier Transform as a mathematical concept is based on the discovery that it is possible to take any periodic function of time  $x(t)$  and resolve it into an equivalent infinite summation of sine waves and cosine waves with frequencies that start at 0 and increase in integer multiples of a base frequency  $f = 1/T$ , where  $T$  is the period of  $x(t)$ . Any wave function can be defined in terms of amplitude,  $A$ , and wavelength,  $\lambda$  or frequency,  $\omega$ . A full description of such a wave also requires definition of a phase,  $\phi$ . A simple one-dimensional wave-function,  $f(t)$ , specifies the height of the wave at any horizontal point  $t$  where  $t$  is defined in terms of wavelength such that  $t=1=\lambda$ . This wave function could be represented as either a sine or a cosine function as follows:

$$f(t) = A \cos 2\pi(\omega t + \phi) \quad (4.2)$$

or

$$f(t) = A \sin 2\pi(\omega t + \phi) \quad (4.3)$$

The term  $2\pi$  appears because there are 2 radians per wavelength. Fourier analysis of complex wave functions dissociates them into a Fourier series of simple wave functions such as  $f(t)$ . We could write a Fourier series containing  $n$  terms as:

$$F(t) = A_0 \cos 2\pi(0t + \phi_0) + A_1 \cos 2\pi(t + \phi_1) \\ + A_2 \cos 2\pi(2t + \phi_2) + \dots + A_n \cos 2\pi(nt + \phi_n) \quad (4.4)$$

or

$$F(t) = \sum_{\omega=0}^n A_{\omega} \cos 2\pi(\omega t + \phi_{\omega}) \quad (4.5)$$

This shows that any complex wave can be expressed as a composite of simpler cosine or sine waves. [47]

Signals may be described as being of the same value either in the time or in the frequency domain. Therefore, it is possible to convert one domain into the other. The mathematical fundament of these conversions is the Fourier Transform.

#### 4.2.2 Modes Analysis

In modes analysis, Fourier transform will be applied to the signal for one day containing 24 hours. So, the period of this signal is 24 h which means that the base frequency  $f$  is  $\frac{1}{24} = 0.0417$  Hz. First, the amplitudes and phase angles of this signal will be evaluated. The signal is reconstructed again by the decomposition of the evaluated amplitudes and phase angles using sum of cosines series. So, the amplitudes and phase angles at integer positive frequencies will be selected for reconstruction of the signal. At the end, an equation containing load consumption as a function of time

will be established. It is found that the first six harmonics are enough to reconstruct the signal. So, the model of each mode will be of the form:

$$F(t) = \sum_{n=0}^6 A_n \cos(n\omega(t-1) + \phi_n) \quad (4.6)$$

where,

- t is the time in hours.
- A is the amplitude.
- n is the frequency number from 0 to 7.
- $\omega$  is the frequency in rad/s which equals to  $2\pi/24$ .
- $\phi$  is the phase angle.

The approach used to model the equations of the modes will be as follows. Every mode will be represented by its average day. Since the days of any mode have similar behavior, this average day is the representative of the mode. Fourier Transform analysis will be applied to this average day using MATLAB program commands. A model of the form of equation 4.6 is built. So, this results into number of models equal to number of modes. Every model is representing a mode. All modes have same form of equation 4.6. The difference is in the values of amplitudes and phase angles. Now, this model is decomposed of two components, namely, dc component at frequency number 0 representing the average value of the signal and is considered as a carrier of the load consumption curve. The other component is the ac component at frequencies from 1 to 6 which represents the daily load shape only. After the model is built, the dc component is removed from the model making the mean value for the entire day to be zero. So, the model is now representing only daily load shape and its curve is placed at the zero axes. Steps of this approach are shown in figure 4.6.

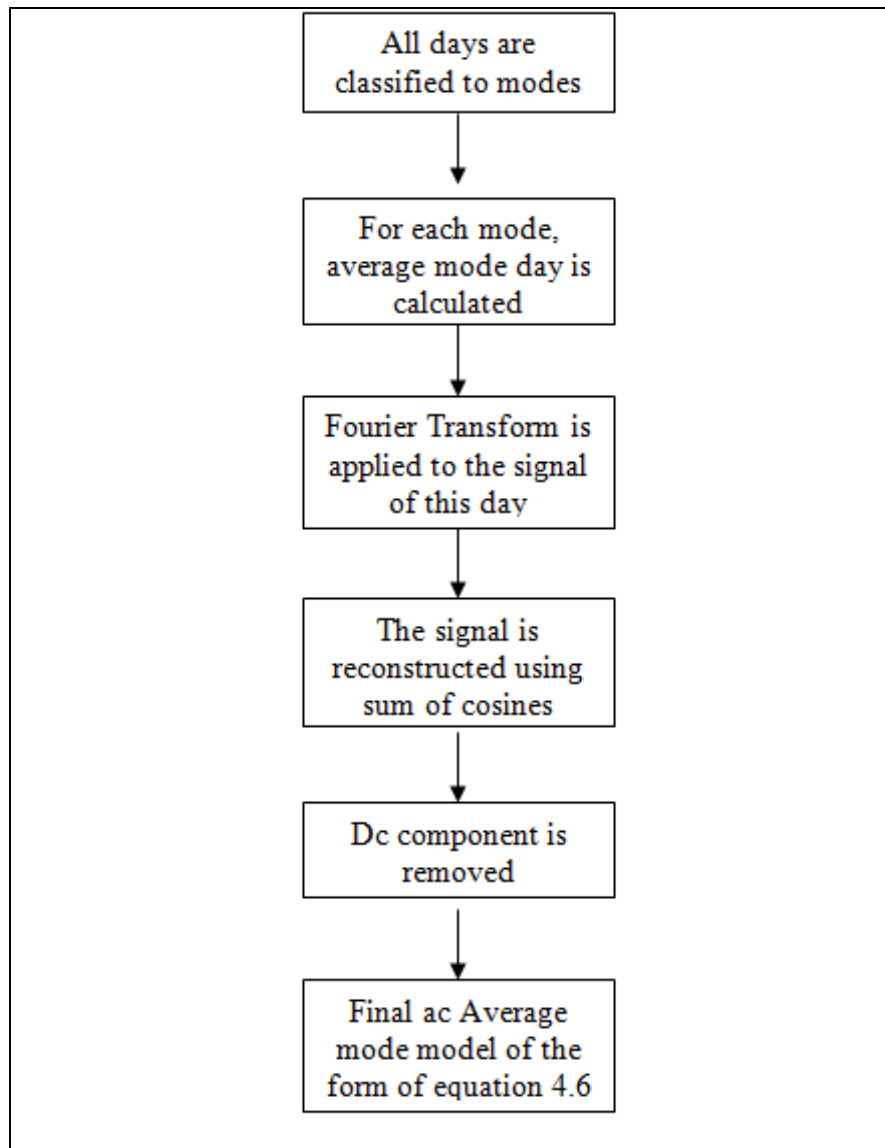


Figure 4.6: Steps used in modes analysis modeling

A sample data, Marafiq, will be used to show the analysis of this approach in details. Years 2009 and 2010 will be used in model building to forecast the year 2011. Figure 4.7 shows the power profile for years 2009 to 10 December 2011 for Marafiq data. Also, figure 4.8 shows the load profile for the year 2010 for Marafiq data along with the components of the signal which are the dc component (average daily power) and the ac component having zero mean value.

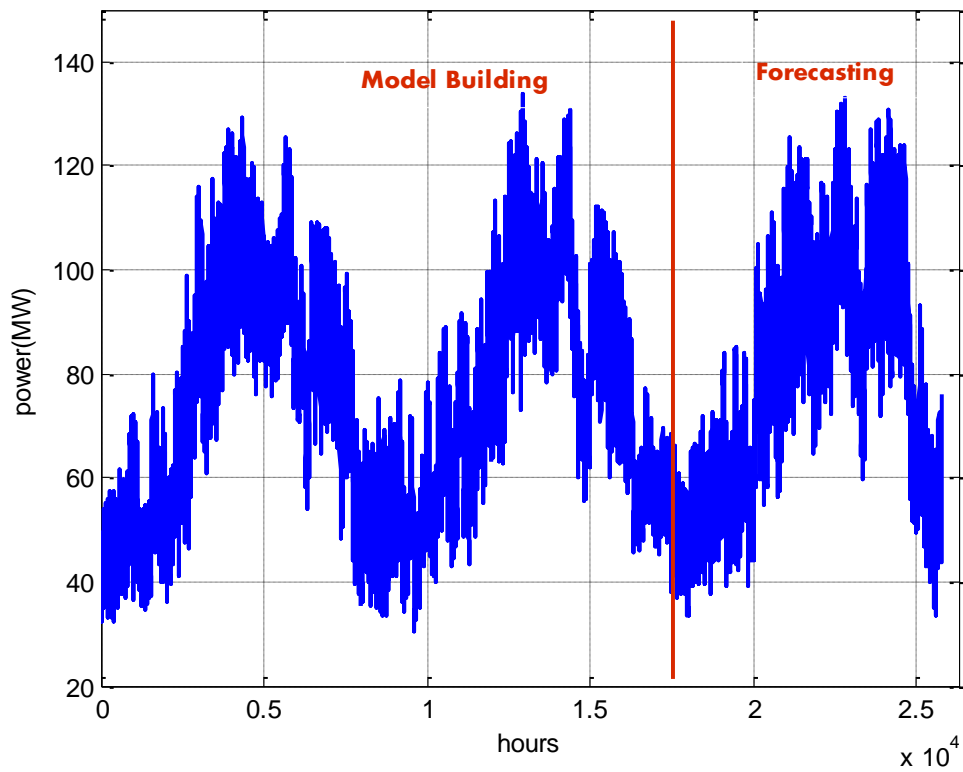


Figure 4.7: Power profile for years 2009 to 10 December 2011 for Marafiq data

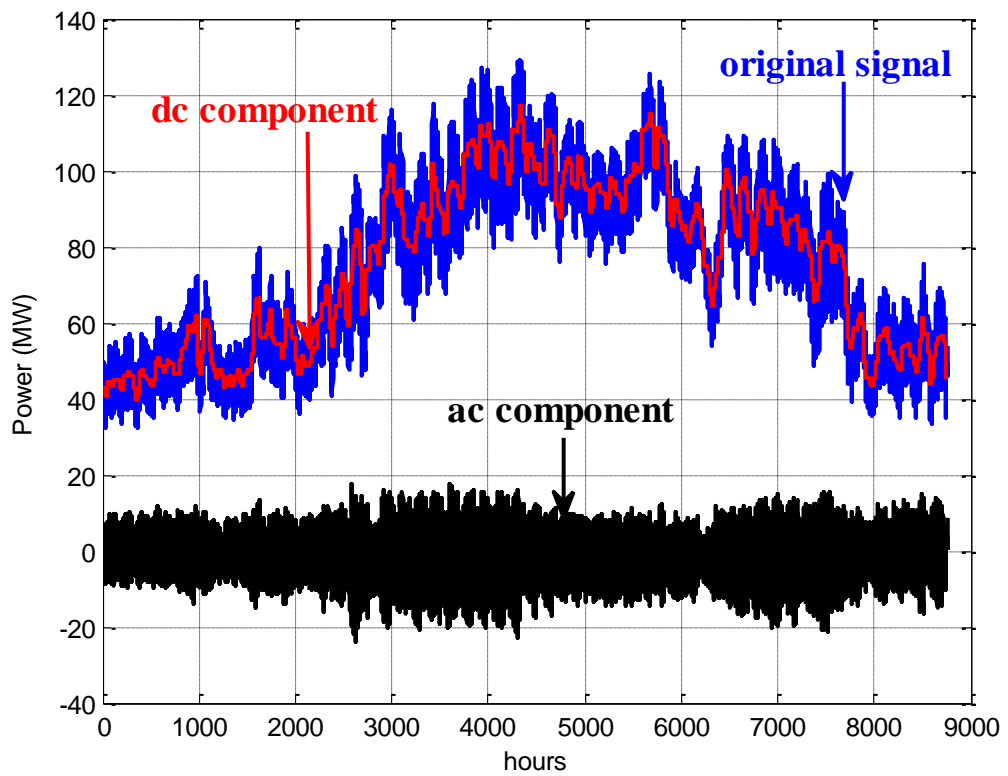


Figure 4.8: Power profile with ac and dc components, Marafiq, 2009

It is clear from figure 4.8 that the signal is segregated into two parts; ac component and dc component from the original power profile. The idea is to identify each mode from other modes. All these modes have zero mean value. Moreover, the dc component will be predicted based on ANN analysis. Both modes and dc component are added together and expected to forecast the behavior of the load.

In next pages, every mode will be analyzed individually. At the end, same model structure will be built for every mode as found in equation 4.6. Harmonics components for each mode are different and these harmonics are the major factors that cause the distinct behavior in the curve between the modes. A sample mode, hot Fridays, will be discussed and explained in details and then all other modes are analyzed in the same way.

#### **4.2.2.1 Hot Fridays Mode**

Hot Fridays mode means all Fridays from schools period characterized by high temperature values. All hot Fridays from years 2009 and 2010 will be displayed as shown in figure 4.9. The similarity between the days of this mode is clear.

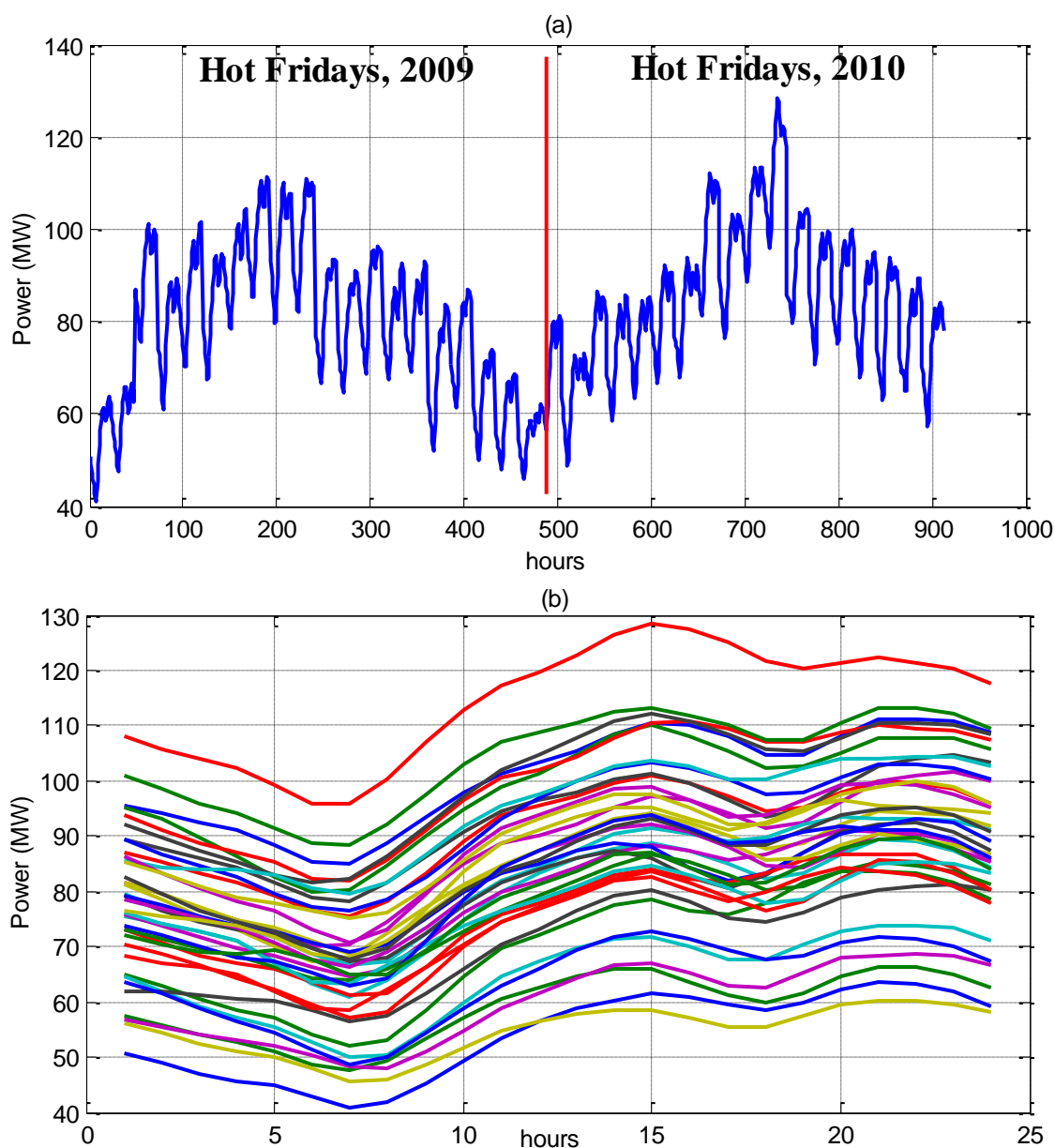


Figure 4.9: (a) Hot Fridays for years 2009 and 2010, Marafiq  
 (b) Hot Fridays similarity for years 2009 and 2010, Marafiq

So, the aim now is to find the daily load curve shape for this mode. Then, the average day for this mode is found. The way is simply by taking the mean of power values at each hour resulting in 24 average power values representing the average mode day. The average mode day for hot Fridays mode is shown in figure 4.10.

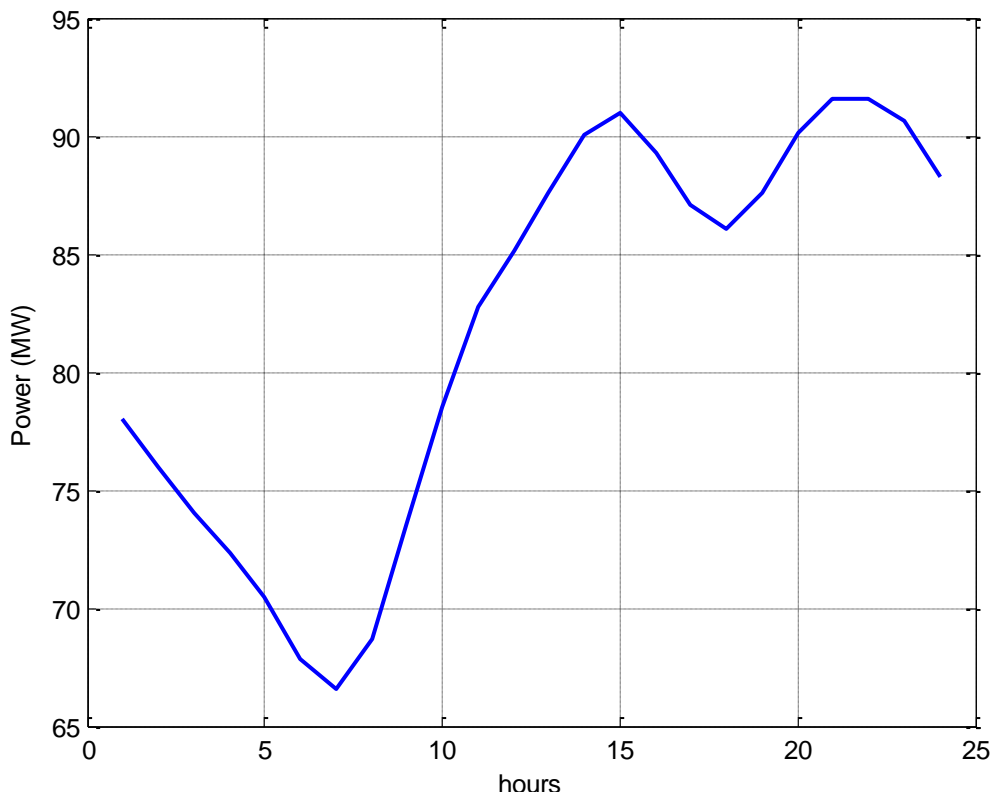


Figure 4.10: Average day for hot Fridays mode

So, this average day is the representative of all days of the mode and it gives information of how the hot Fridays mode will be in the forecasted year, 2011. Then, Fourier Transform analysis will be applied to this average day to decompose its signal to its harmonics as seen from figure 4.11. Amplitudes and phase angles values for this signal are shown in table 4.3.



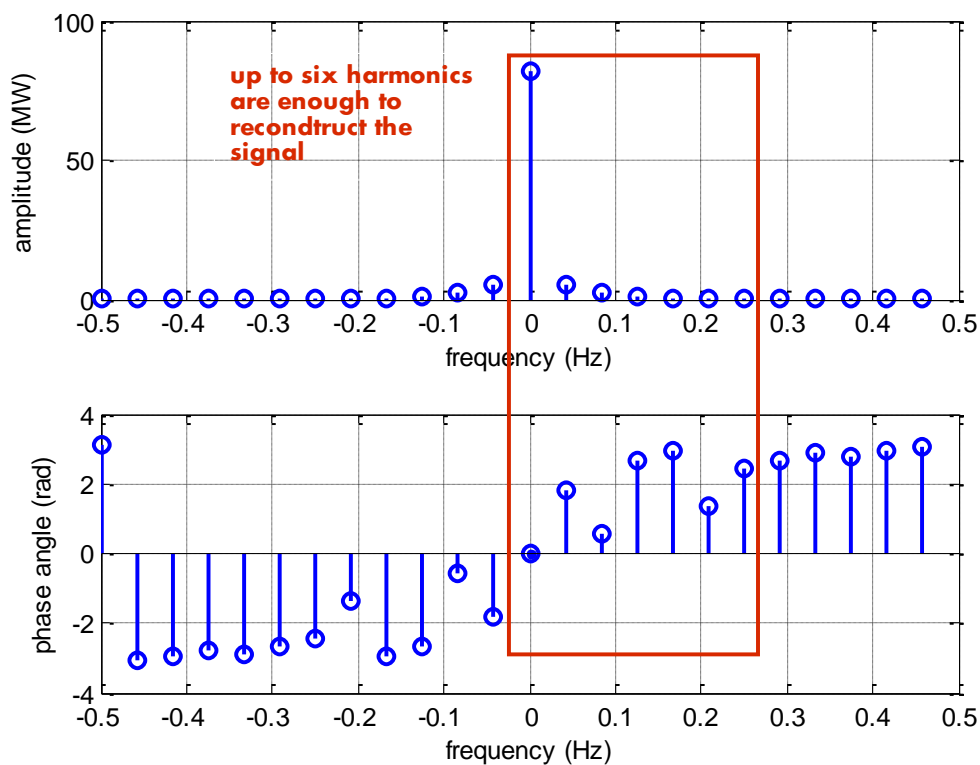


Figure 4.11: Amplitudes and phase angles of the average mode day

Table 4.5: Amplitudes and phase angles values for the average day of hot Fridays mode

Harmonic number	0 (dc comp)	1	2	3	4	5	6
Amplitude	81.8616	5.448	2.1344	0.8586	0.6978	0.3843	0.2363
Phase angle	0	1.796	0.5895	2.6735	2.9737	1.3374	2.4156

At the end, the dc component (the amplitude value at zero frequency) will be removed from the model which makes the mean value of the whole day equals zero.

Figure 4.12 shows the final modeled general average day for hot Fridays mode.

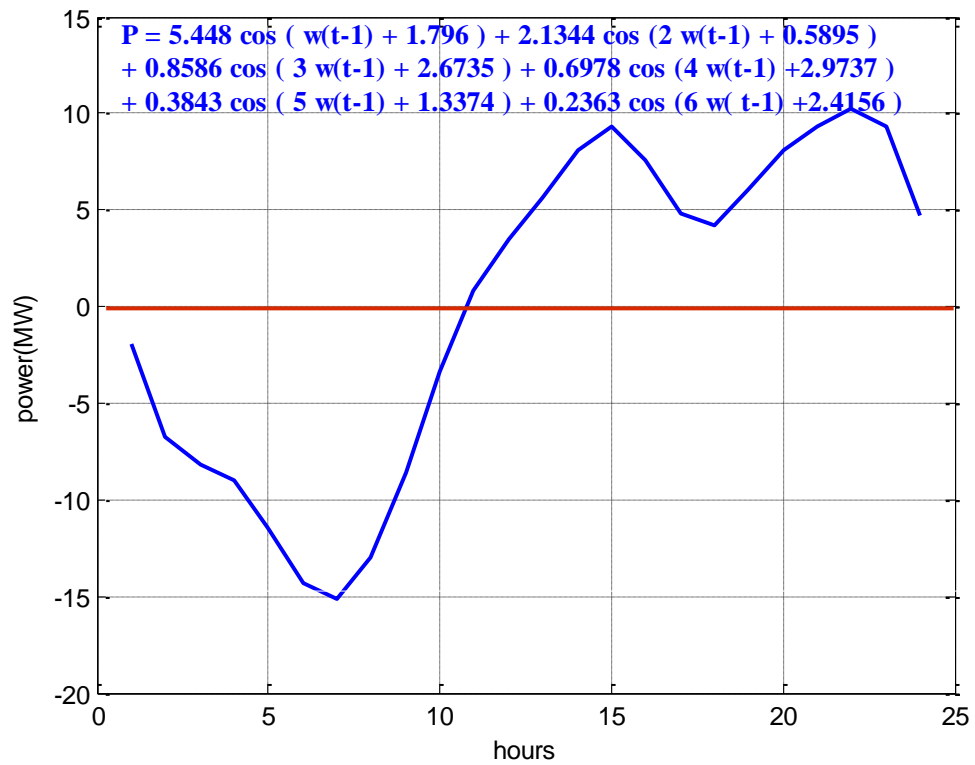


Figure 4.12: Final average daily modeled load curve for hot Fridays mode

So, same approach applied in hot Fridays mode will be applied to other modes.

All other modes analysis will be shown in figures 4.13 to 4.26.

#### 4.2.2.2 Ramadan Mode

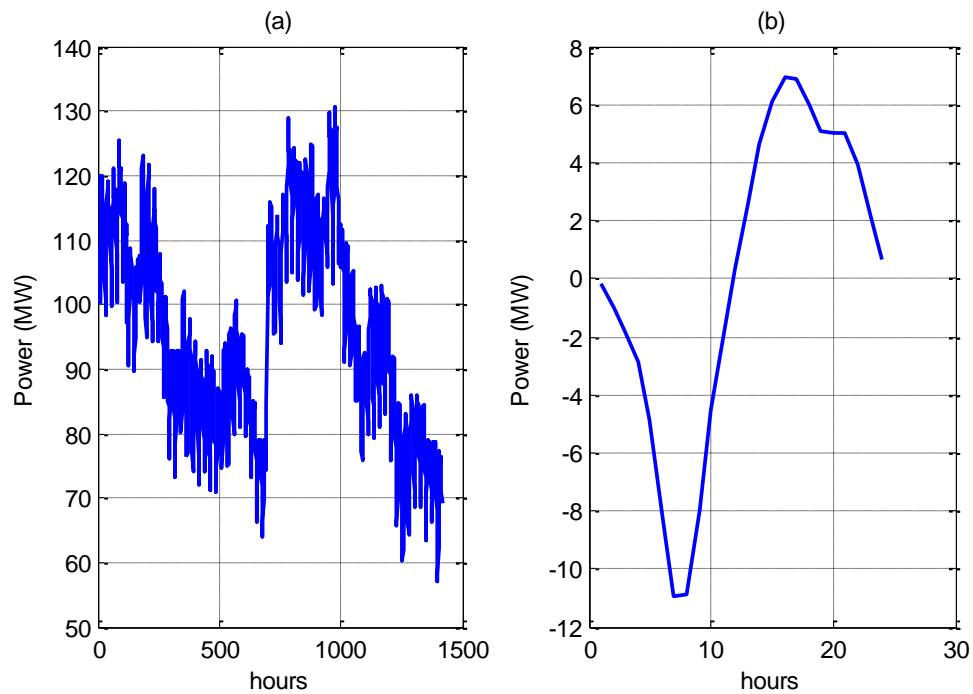


Figure 4.13: (a) Ramadan days for years 2009 and 2010  
(b) Final average daily modeled load curve for Ramadan mode

#### 4.2.2.3 Eid Feter Day Mode

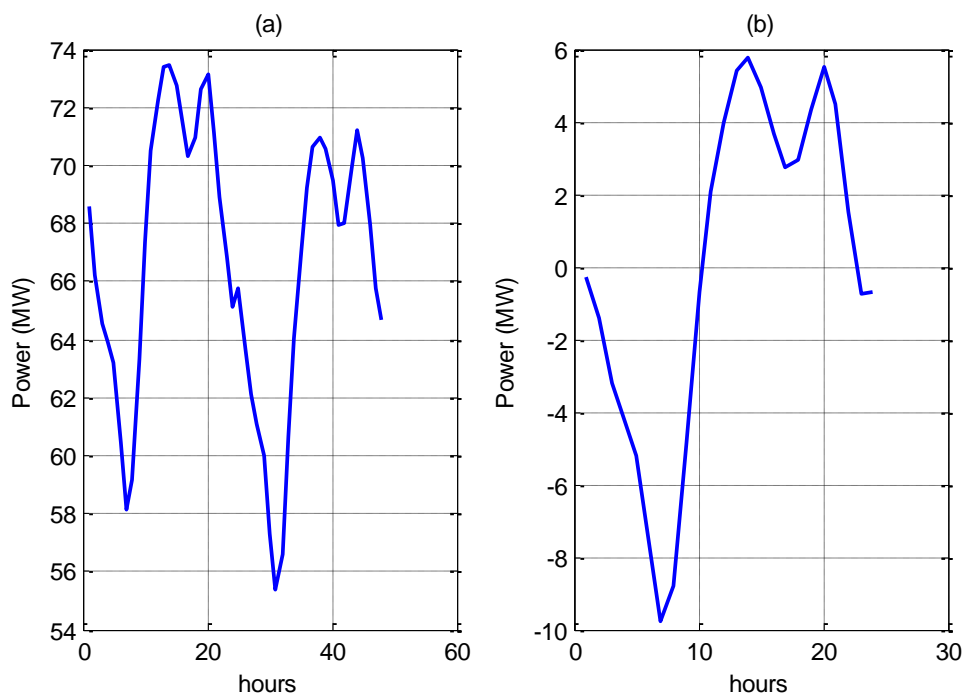


Figure 4.14: (a) Eid Feter days for years 2009 and 2010  
(b) Final average daily modeled load curve for Eid Feter mode

#### 4.2.2.4 After Eid Feter Days Mode

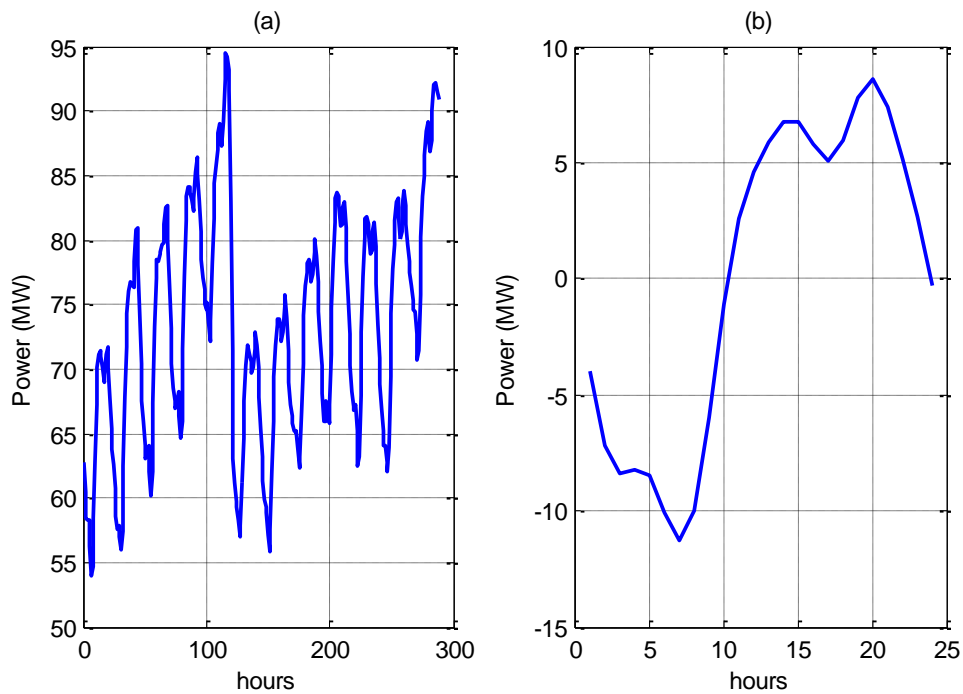


Figure 4.15: (a) After Eid Feter days for years 2009 and 2010  
(b) Final average daily modeled load curve for After Eid Feter days mode

#### 4.2.2.5 Eid Hajj Day Mode

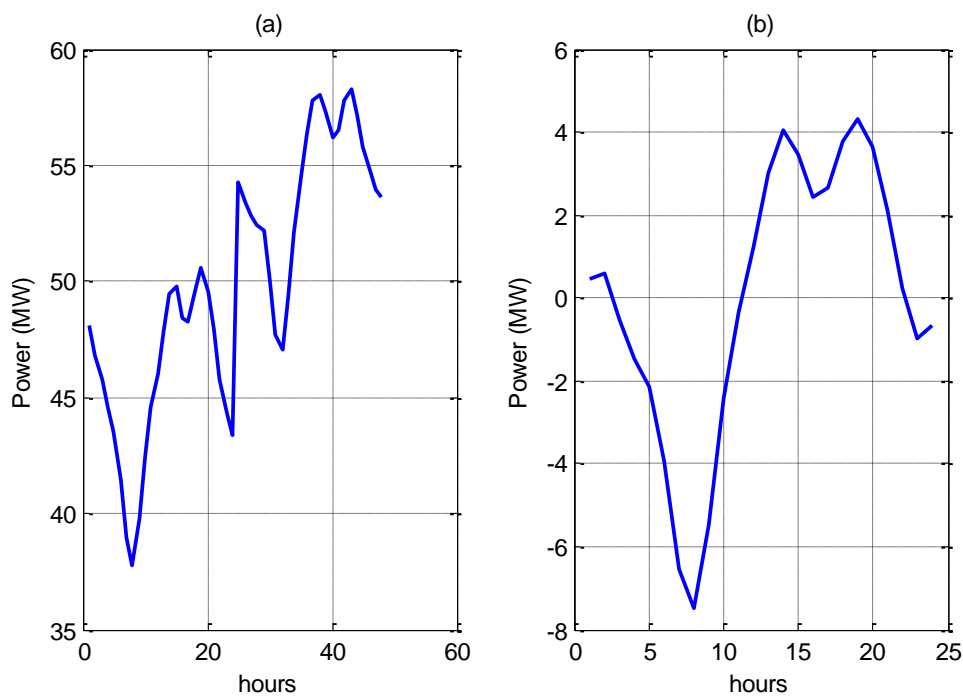


Figure 4.16: (a) Eid Hajj days for years 2009 and 2010  
(b) Final average daily modeled load curve for Eid Hajj mode

#### 4.2.2.6 After Eid Hajj Days Mode

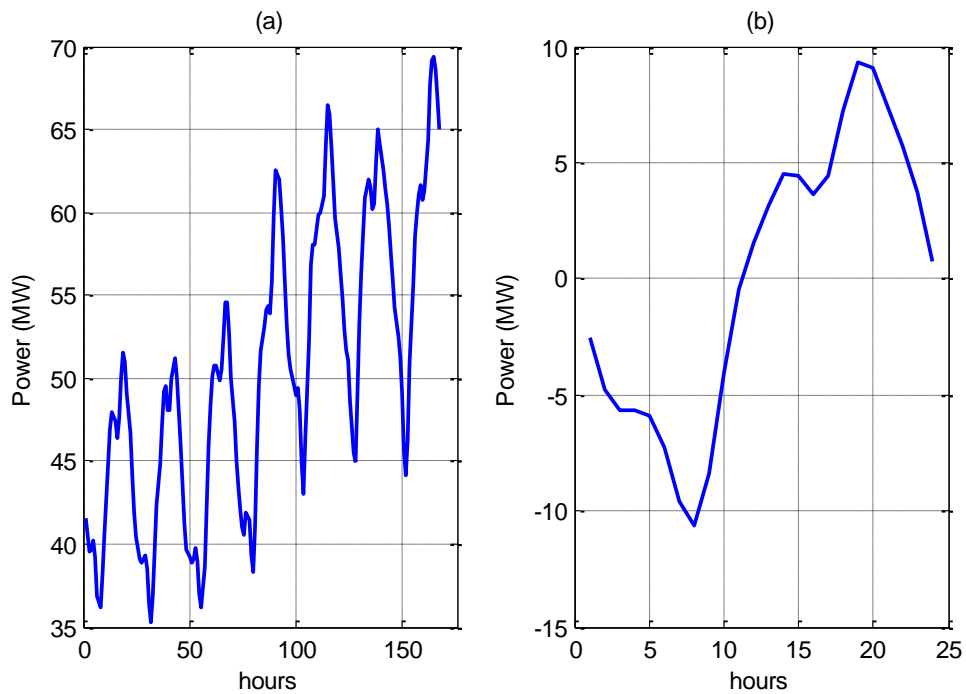


Figure 4.17: (a) After Eid Hajj days for years 2009 and 2010  
(b) Final average daily modeled load curve for After Eid Hajj mode

#### 4.2.2.7 Hot Week Days Mode

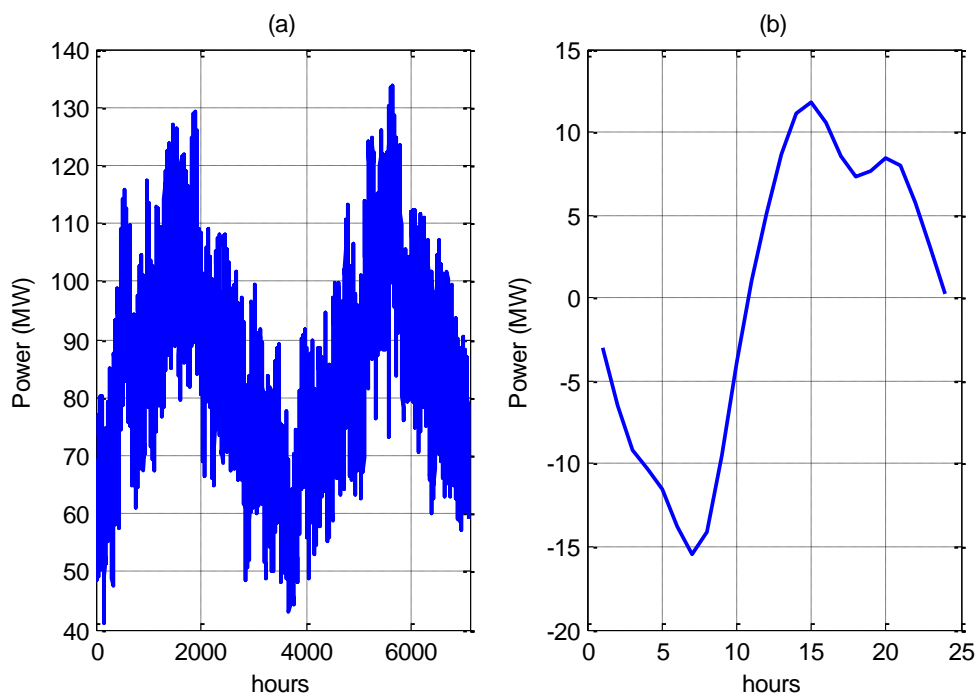


Figure 4.18: (a) Hot week days for years 2009 and 2010  
(b) Final average daily modeled load curve for hot week days mode

#### 4.2.2.8 Hot Thursdays Mode

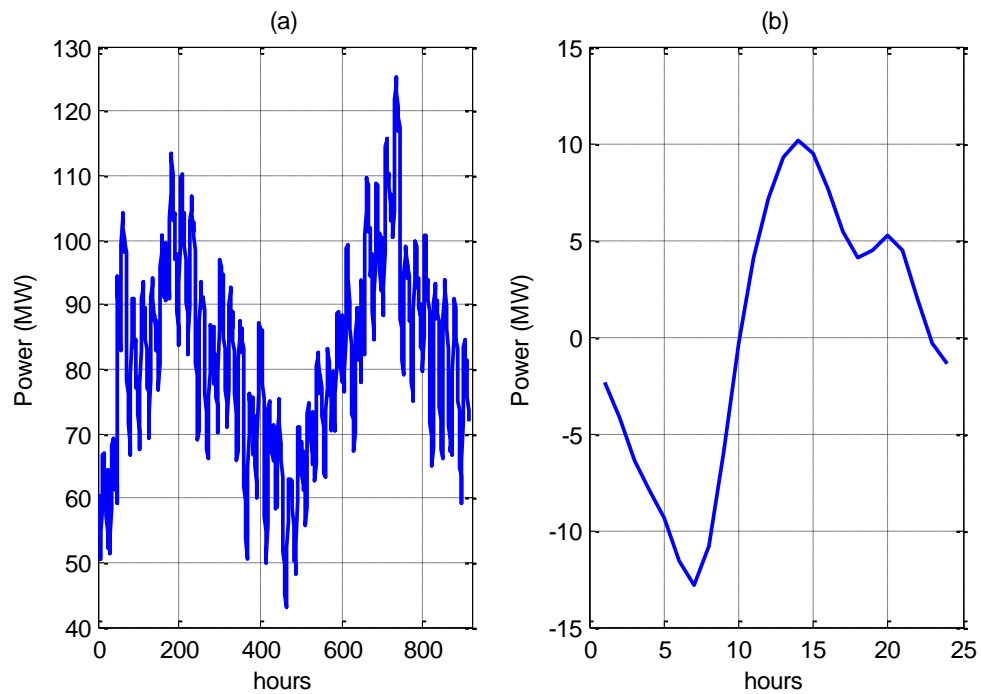


Figure 4.19: (a) Hot Thursdays for years 2009 and 2010  
(b) Final average daily modeled load curve for hot Thursdays mode

#### 4.2.2.9 Summer Vacation Week Days Mode

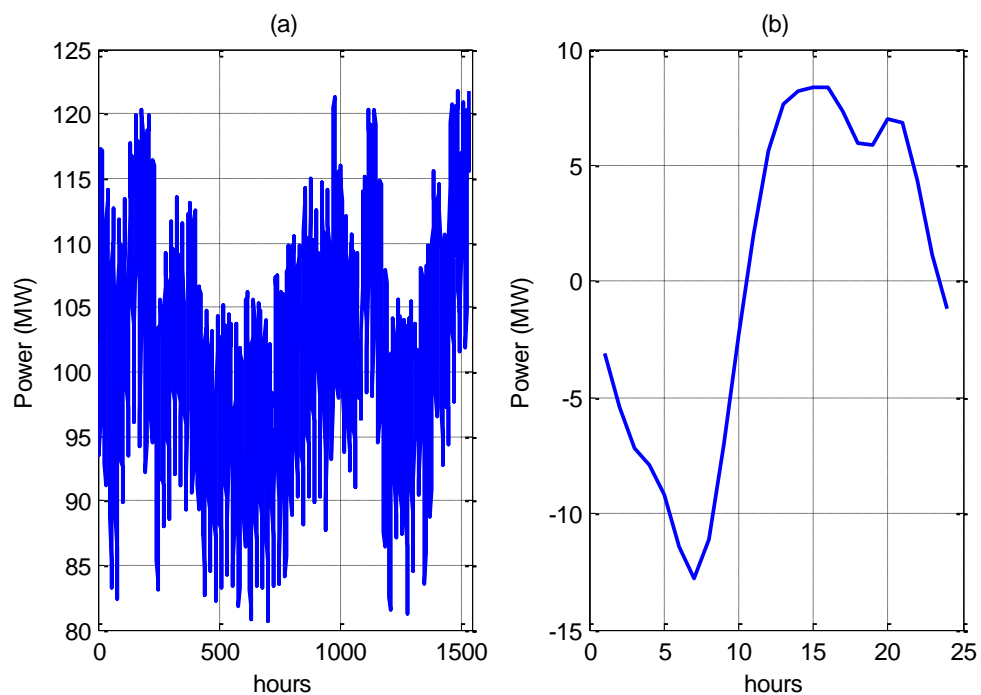


Figure 4.20: (a) Summer vacation week days for years 2009 and 2010  
(b) Final average daily modeled load curve for summer vacation week days mode

#### 4.2.2.10 Summer Vacation Thursdays Mode

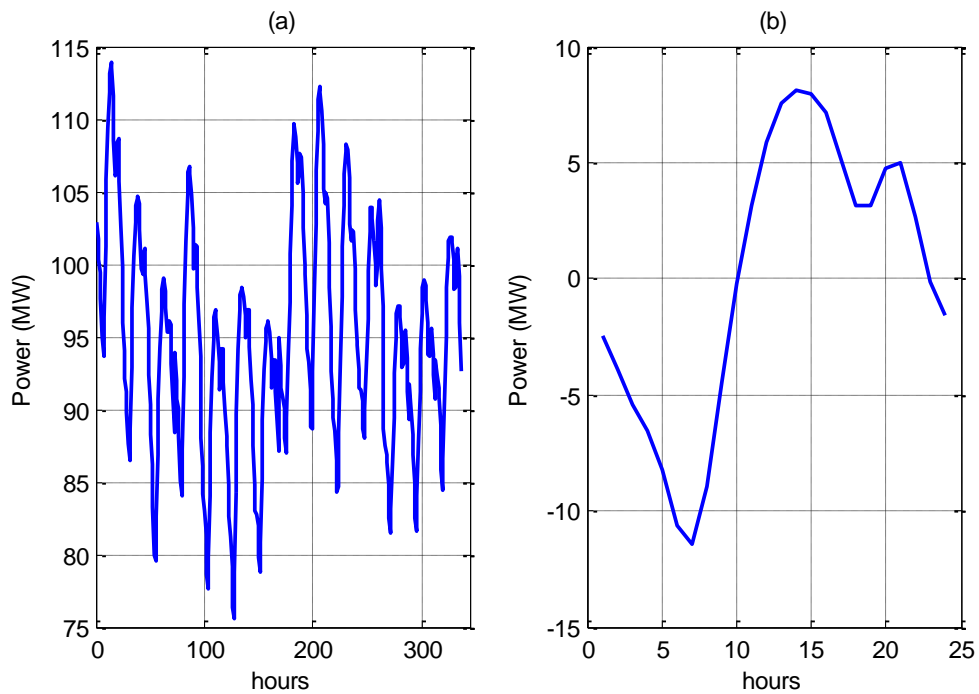


Figure 4.21: (a) Summer vacation Thursdays for years 2009 and 2010  
(b) Final average daily modeled load curve for summer vacation Thursdays mode

#### 4.2.2.11 Summer Vacation Fridays Mode

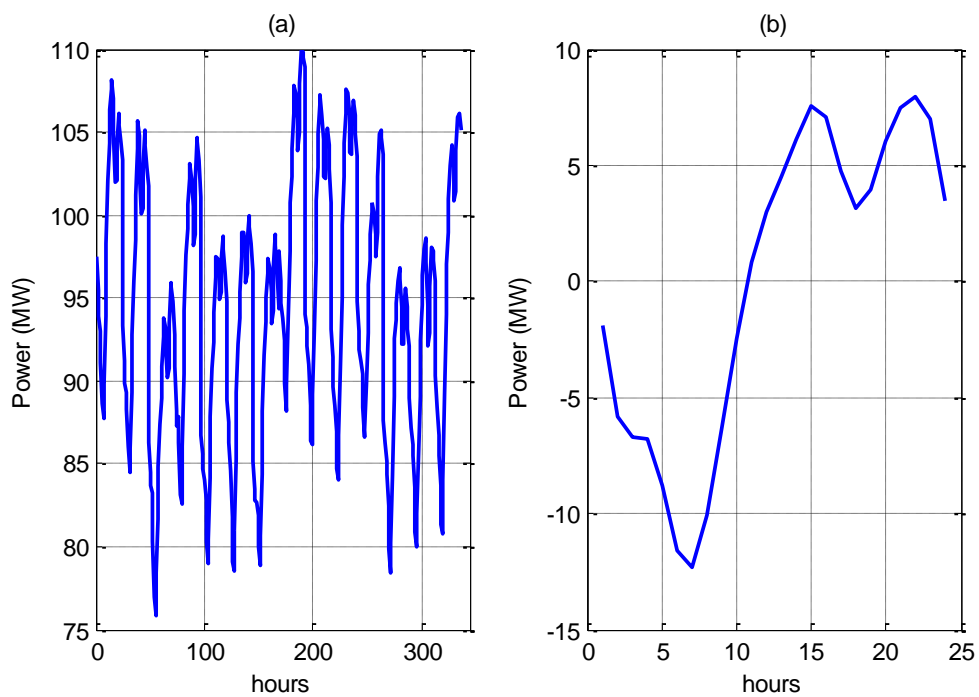


Figure 4.22: (a) Summer vacation Fridays for years 2009 and 2010  
(b) Final average daily modeled load curve for summer vacation Fridays mode

#### 4.2.2.12 Mid-Year Vacation Mode

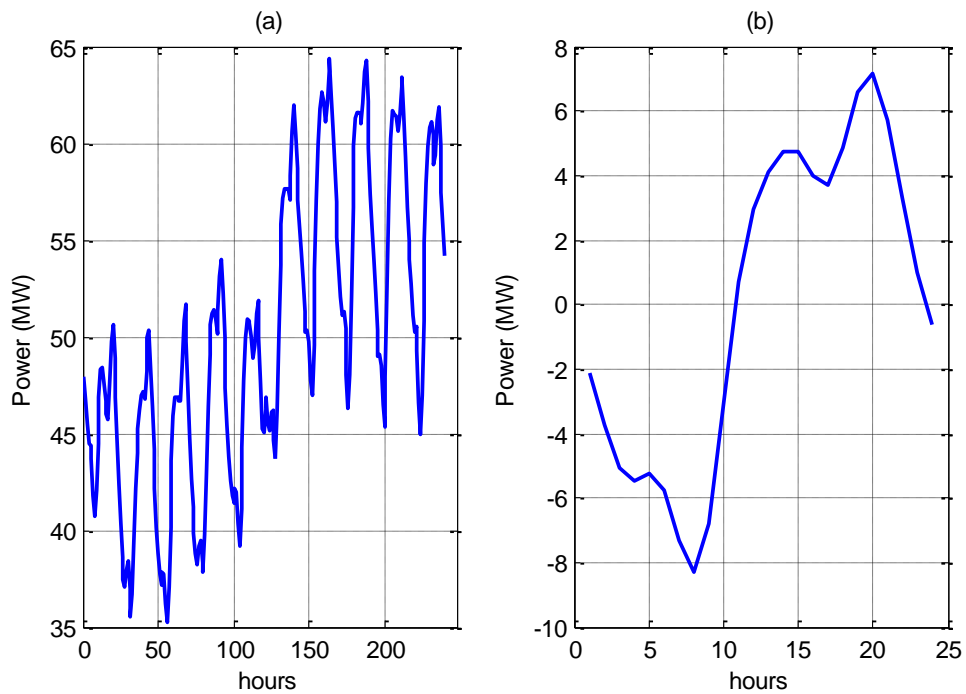


Figure 4.23: (a) Mid-year vacation days for years 2009 and 2010  
(b) Final average daily modeled load curve for mid-year vacation mode

#### 4.2.2.13 Cold Week Days Mode

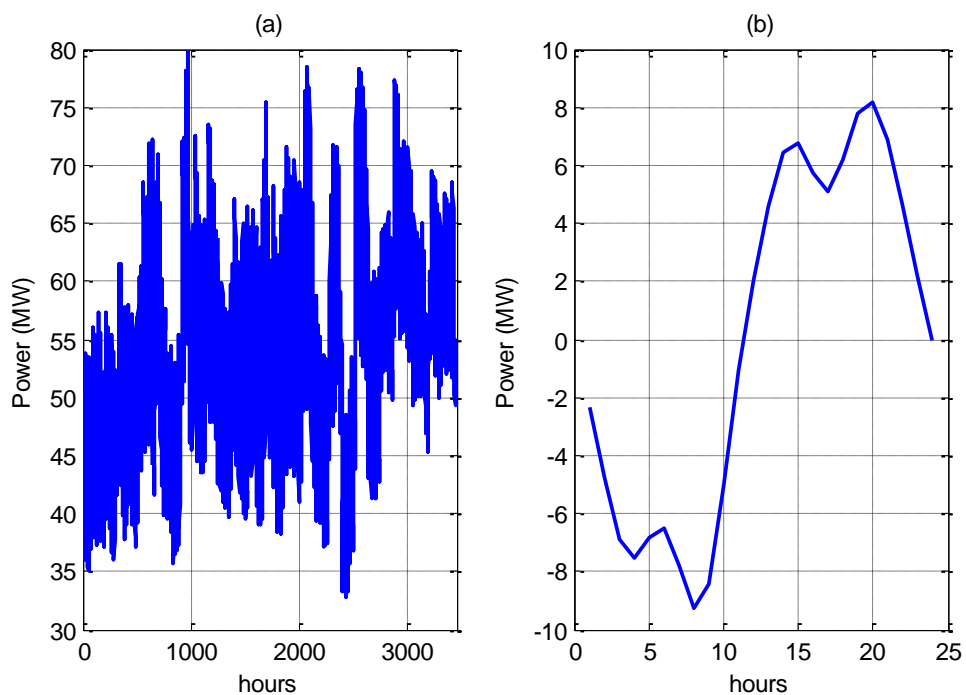


Figure 4.24: (a) Cold week days for years 2009 and 2010  
(b) Final average daily modeled load curve for cold week days mode



#### 4.2.2.14 Cold Thursdays Mode

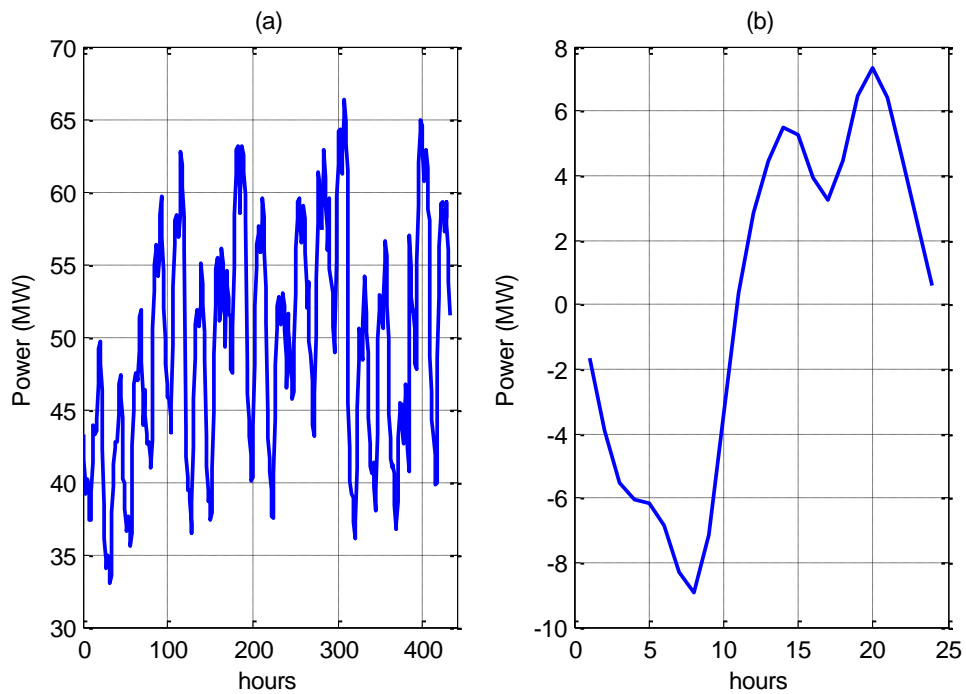


Figure 4.25: (a) Cold Thursdays for years 2009 and 2010  
(b) Final average daily modeled load curve for cold Thursdays mode

#### 4.2.2.15 Cold Fridays Mode

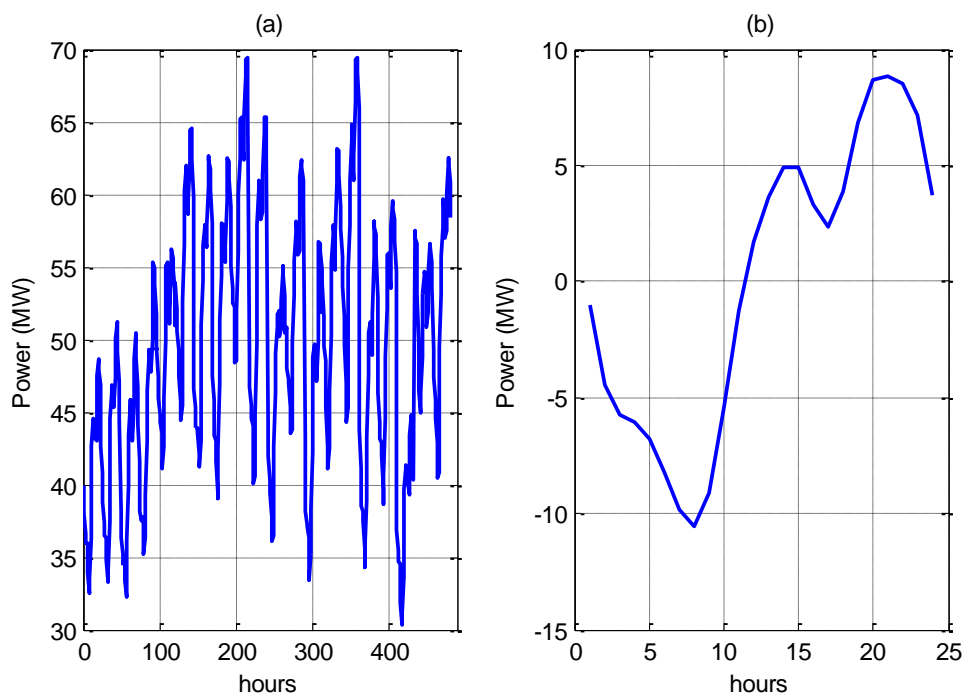


Figure 4.26: (a) Cold Fridays for years 2009 and 2010  
(b) Final average daily modeled load curve for Cold Fridays mode

So, now, every mode is represented by its average day. Each average day is modeled by the structure of equation 4.6. Therefore, by specifying the mode number for any day of the forecasted year, 2011, its daily load curve shape is now ready and can be taken from the previous figures. All of these modeled days are placed at the zero axes and have zero mean value. So, a clear picture of how the shape of each day in 2011 is available now and all of these days are “waiting” for the carrier function which is the average daily load consumption value that shifts or carries the mode day to the original level. Next step is forecasting next day average load consumption for 2011 which will be added to the mode days to reach to the final desired model.

#### **4.2.3 Carrier Analysis**

In carrier analysis, next day average power will be forecasted using NN analysis. By assuming that we are at day  $d-1$ , the aim is to forecast the average power value for next day  $d$ . The mode number for day  $d$  is known and its shape will be taken from its respected mode shape shown in modes analysis section. Then, by simple addition operation, this value will ‘carry’ the shape of the mode day for the day  $d$ . As explained in NN analysis in section 4.2.1, the same structure for the used models for STLF will be used here. For all sources of data, the model contains one hidden layer with 5 hidden neurons. The inputs to the model are day, month, year, day type, day sequence through the year, mode number and expected average temperature for the forecasted day  $d$ . Also, average temperature, humidity and average power for the previous seven days to the forecasted day are included in the inputs. The output is the average power for day  $d$ . This is shown in figure 4.27.

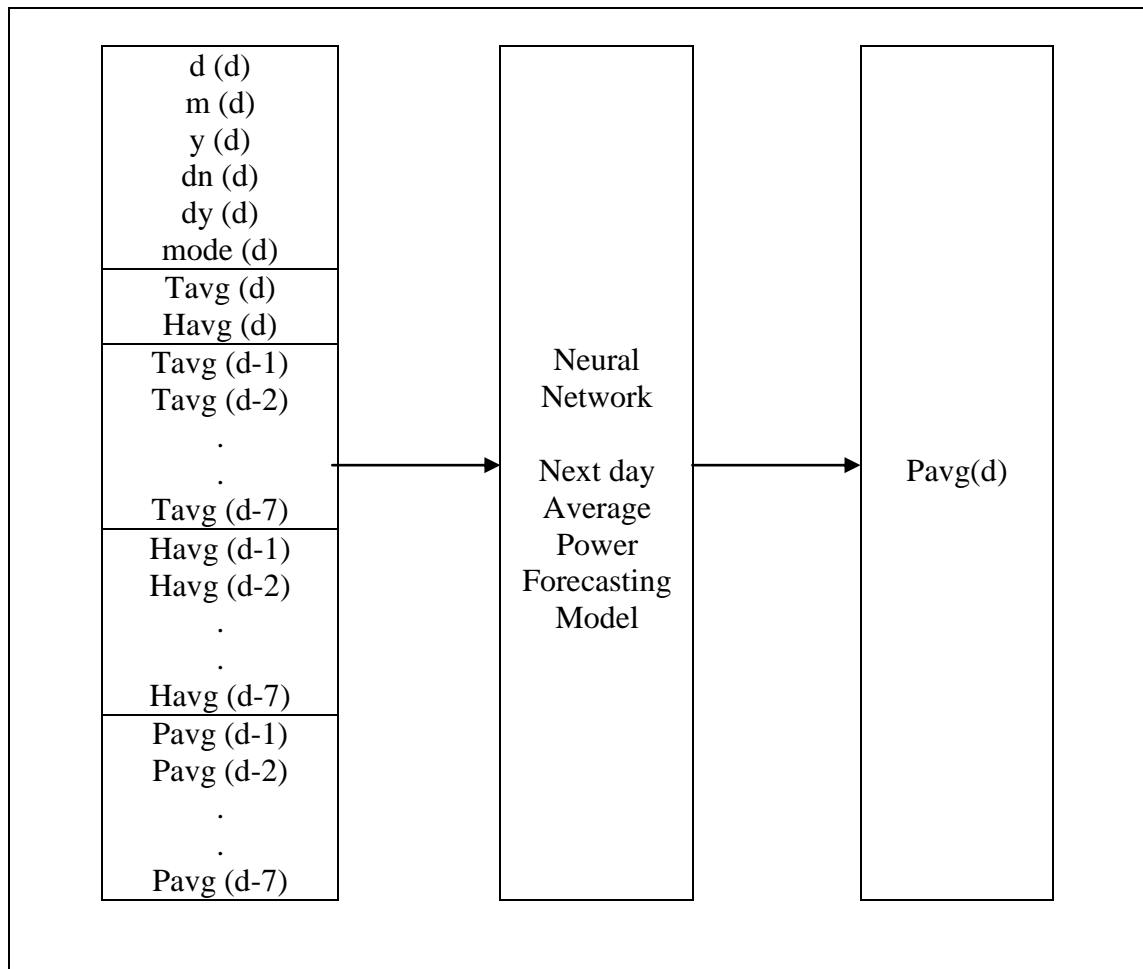


Figure 4.27: Input configuration for next day average power forecasting

Finally, after evaluating next day average power, it will be added to the modeled equation for the mode of the day  $d$  to reach to the final model that will give the power values for all 24 hours for day  $d$  according to the equation:

$$P(d) = Pavg(d) + Pmodel\_mode(d) \quad (4.7)$$

### **4.3 Summary and Conclusions of the Chapter**

The following points have been addressed in this chapter:

- The approaches used in this study are defined to be ANN analysis and hybrid analytical model.
- Every method is defined and explained individually.
- In NN model, the forecasting is for next hour and next day load forecasting and the inputs for each model are defined.
- In the hybrid analytical model, it is divided to two parts. The first part is modes analysis to predict only the daily load curve shape of the forecasted day having zero mean value.
- The second part is forecasting next day average power and its role is to carry the ac mode day shape to the actual level.
- Finally, the two parts values are combined and added to reach to the final model which is for next hour and next day load forecasting.

## **CHAPTER 5**

### **RESULTS AND ANALYSIS**

In this chapter, the results and analyses of each approach mentioned previously will be presented. The data results shown in this chapter are for SEC and Marafiq data. USA data will be analyzed in chapter 6 to compare its results with published paper results using same set of data. Every data source will be analyzed individually to make a comparison for the results obtained from each approach. In NN approach, two models are analyzed, namely, next hour and next day load forecasting models. In hybrid analytical model, next hour and next day models will be the same. For next hour model, only the value of the mode average day at the forecasted hour,  $h$  is evaluated. However, in next day model, the entire mode average day at all 24 hours is calculated. SEC data will be analyzed first, and then Marafiq data analyses and results will be presented.

The load forecast is compared to the actual load data and the error is calculated. The mean absolute percentage error (MAPE) is used to evaluate the performance of these models. It is defined as:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|t_i - a_i|}{t_i} \times 100 \quad (5.1)$$

where  $t_i$  is the actual load (target value), and  $a_i$  is the forecasted load (output value),  $n$  is the number of data points.

## 5.1 SEC Data

In this set of data, the used data for training and model building are from 2001 up to 2004, whereas the forecasted year is 2005. Typical four intervals selected from different seasons will be shown and forecasted using all models. Each interval is a one week period starting from Saturday to Friday. The typical chosen dates for these seasons are depicted in table 5.1.

Table 5.1: The selected dates to represent seasons for all models, SEC data

Season	Date	
	From	To
Entire Cold Week	19/3/2005	25/3/2005
Entire Hot Week	10/9/2005	16/9/2005
Ramadan	8/10/2005	14/10/2005
Summer Vacation	6/8/2005	12/8/2005

The selected cold and hot weeks are complete weeks starting from Saturday to Friday in schools period.

### 5.1.1 Next Hour Load Forecasting

As mentioned previously, two techniques are used for next hour load forecasting which are ANN and hybrid analytical models. Firstly, ANN model results are shown. Then, hybrid analytical model results are analyzed. After that, analysis and comparison of the two approaches are presented.

#### 5.1.1.1 Neural Network Model Approach

The approach, process and inputs variables for this model were shown in details in chapter 4. Comparison between the ANN model output and the actual load, in addition to MAPE values for the four intervals are shown in figures 5.1 to 5.4.

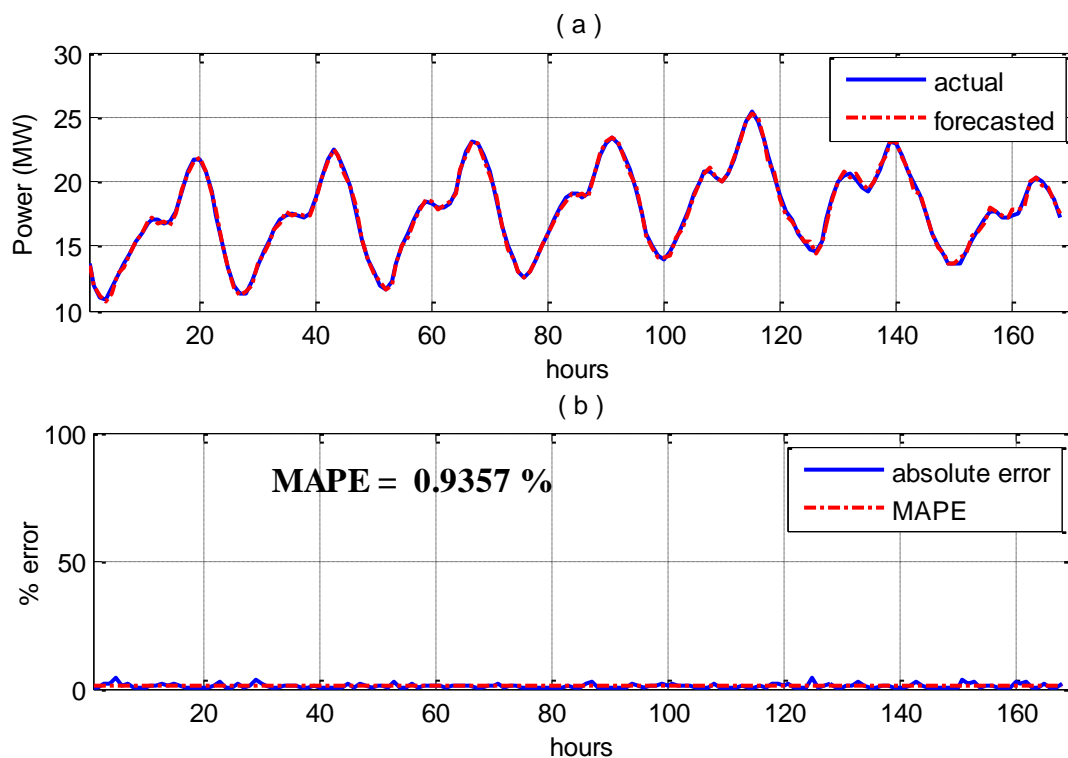


Figure 5.1: a) Actual and forecasted load for cold week period, SEC, 2005  
b) Absolute error and MAPE, next hour, NN

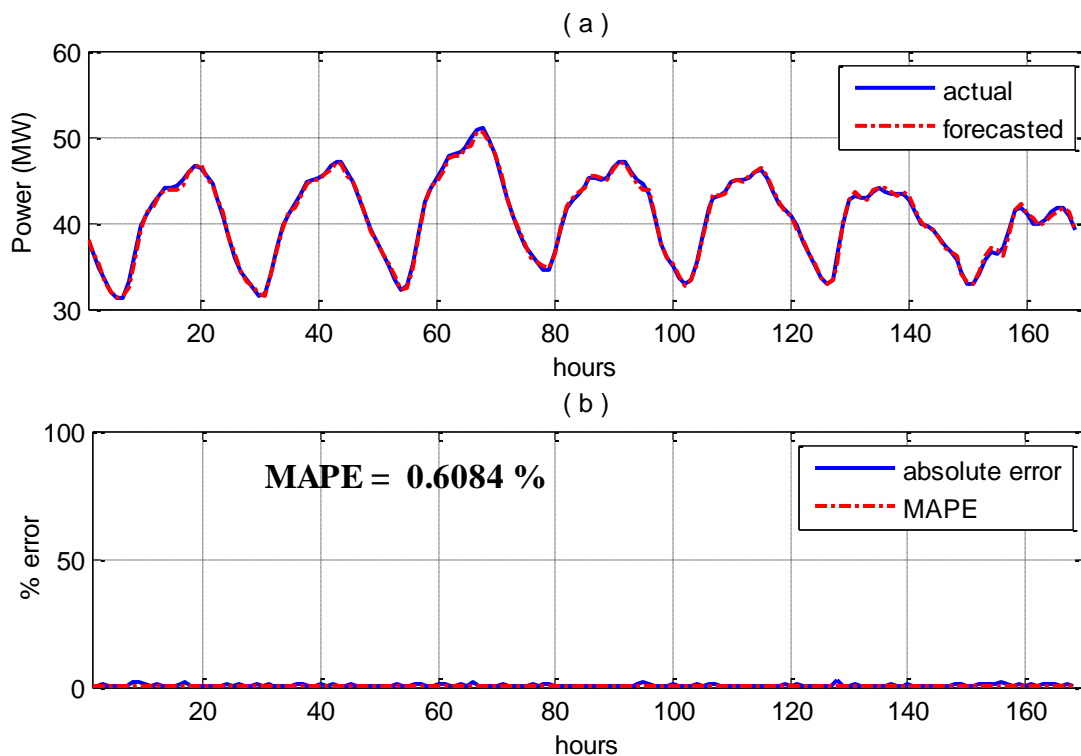


Figure 5.2: a) Actual and forecasted load for hot week period, SEC, 2005  
b) Absolute error and MAPE, next hour, NN

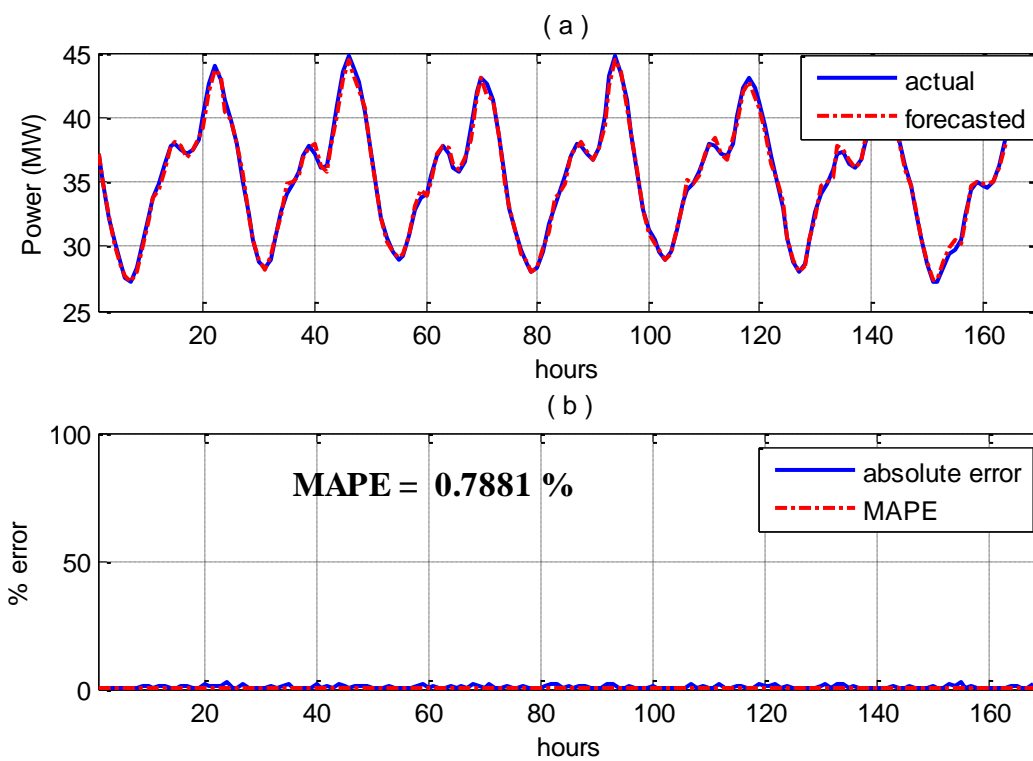


Figure 5.3: a) Actual and forecasted load for Ramadan season, SEC, 2005  
b) Absolute error and MAPE, next hour, NN



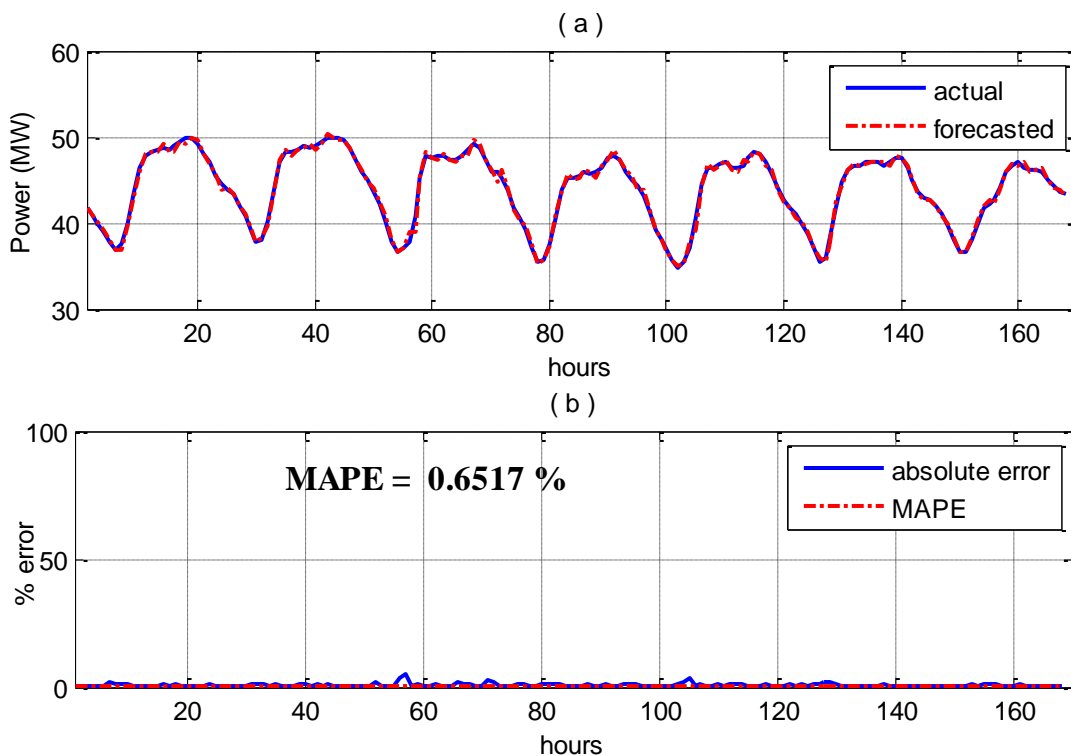


Figure 5.4: a) Actual and forecasted load for summer vacation season, SEC, 2005  
b) Absolute error and MAPE, next hour, NN

So, next hour load forecasting model performance is tested for one week in four different seasons; cold week working period, hot week working period, Ramadan and summer vacation, which will evaluate the model performance across different load profiles. The performance of the model gives accurate results for implementation. MAPE for all four intervals varies between 0.6084 % and 0.9357 % in different load and weather conditions, different calendar times, day types and through special events. This indicates that the model is valid for application through the whole time horizon.

### 5.1.1.2 Hybrid Analytical Model Approach

Comparison between the hybrid analytical model output and the actual load, in addition to MAPE values for the four intervals are shown in figures 5.5 to 5.8.

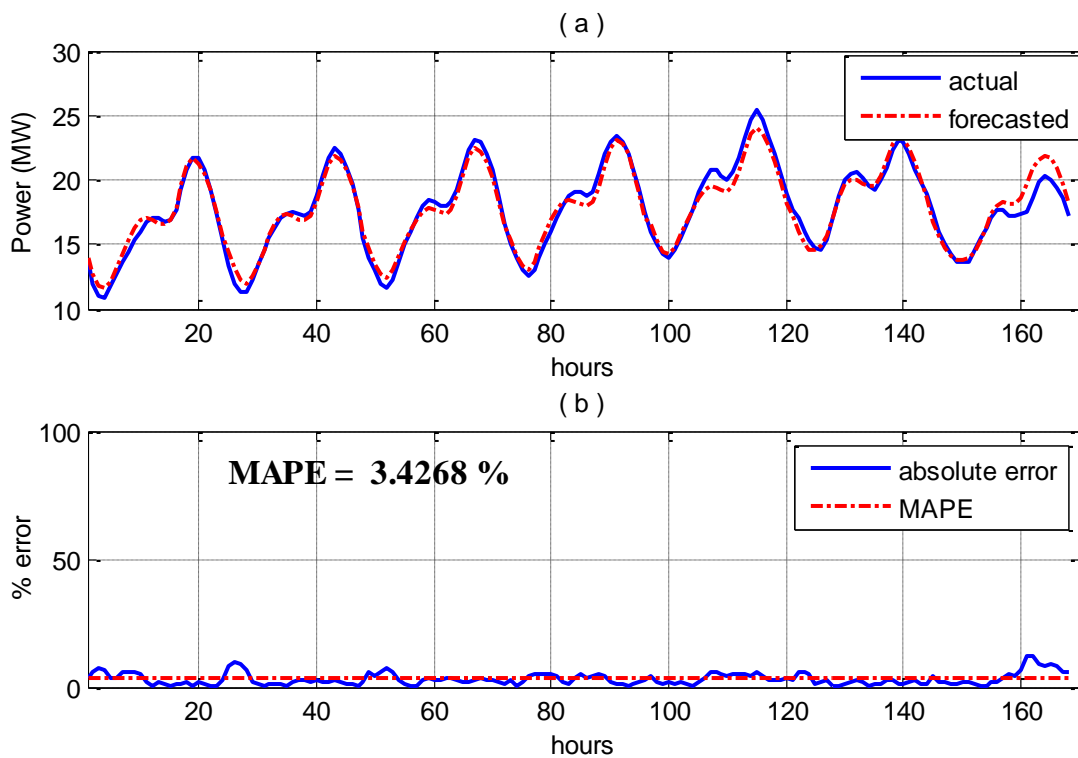


Figure 5.5: a) Actual and forecasted load for cold week period, SEC, 2005  
b) Absolute error and MAPE, next hour, analytical model

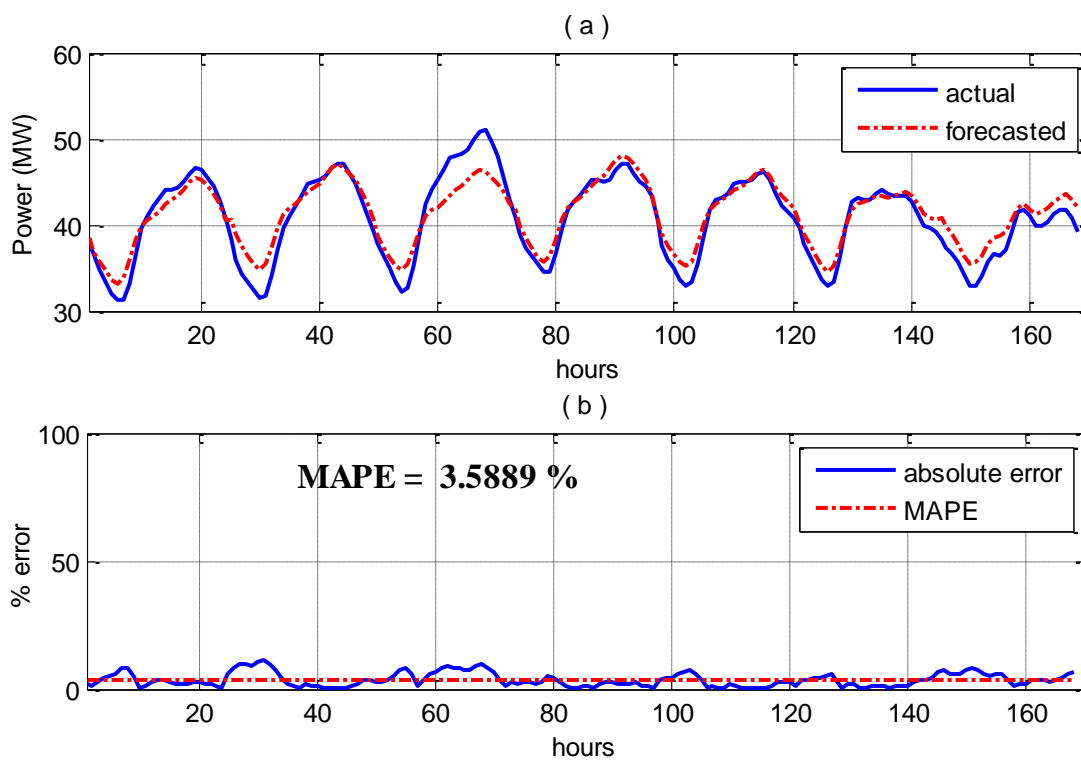


Figure 5.6: a) Actual and forecasted load for hot week period, SEC, 2005  
b) Absolute error and MAPE, next hour, analytical model

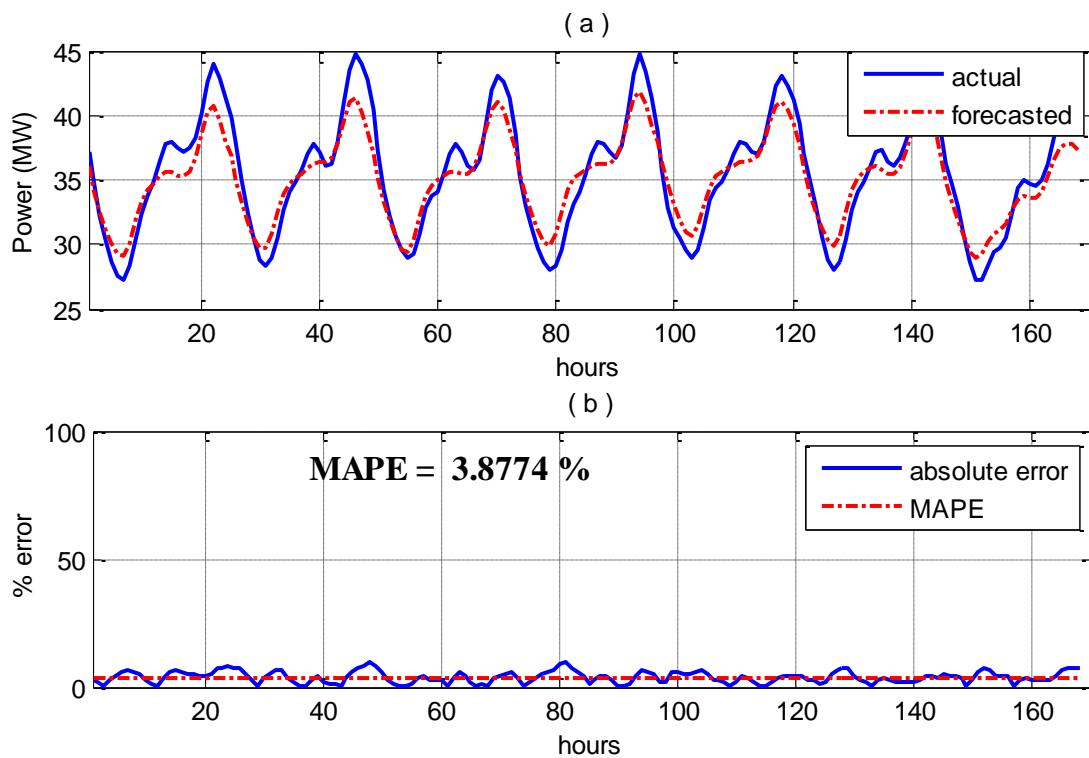


Figure 5.7: a) Actual and forecasted load for Ramadan season, SEC, 2005  
 b) Absolute error and MAPE, next hour, analytical model

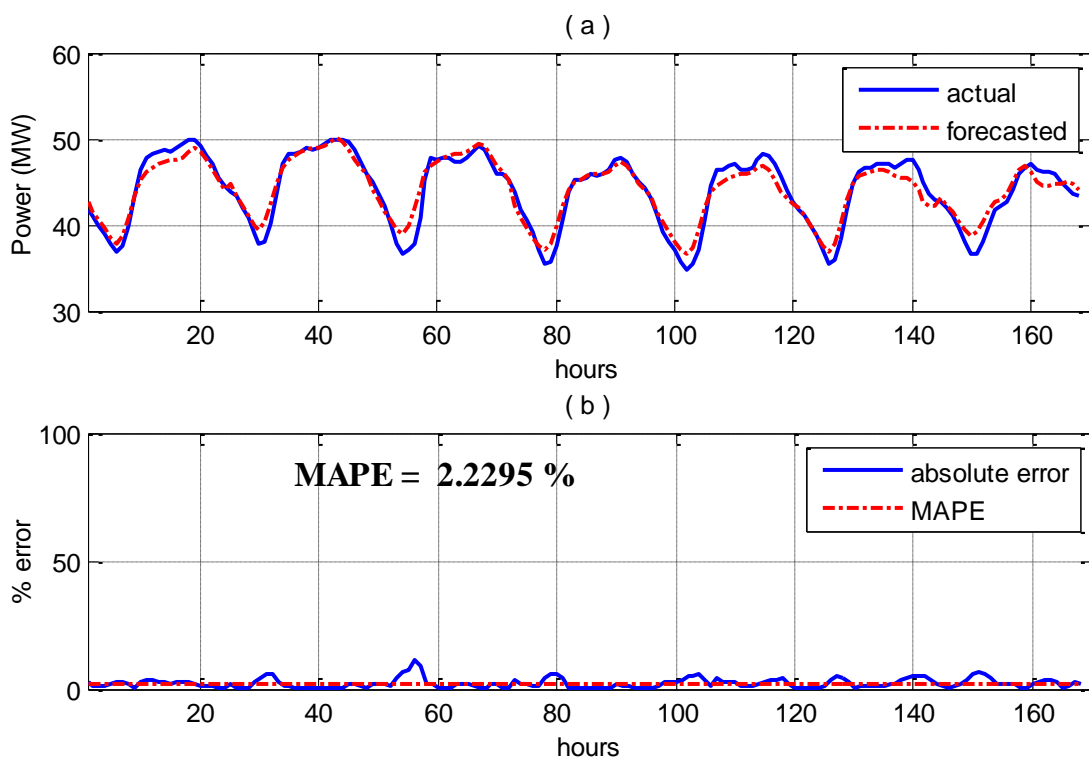


Figure 5.8: a) Actual and forecasted load for summer vacation season, SEC, 2005  
 b) Absolute error and MAPE, next hour, analytical model

It is clear from the previous figures that ANN model achieved better results than the hybrid analytical model. While ANN model results are very accurate, the results obtained using the hybrid analytical model are reasonable ranging from 2.22 % and 3.8 %.

### 5.1.2 Next Day Load Forecasting

As done in next hour model, two main approaches will be used to forecast next day load. First, neural network model approach results will be shown in figures 5.9 to 5.12. Then, the hybrid analytical model approach results will be displayed in figures 5.13 to 5.16. Moreover, results obtained using ANN iterative model are shown in figures 5.18 to 5.21. After that, comparison analysis of the three approaches will be presented.

#### 5.1.2.1 Neural Network Model Approach

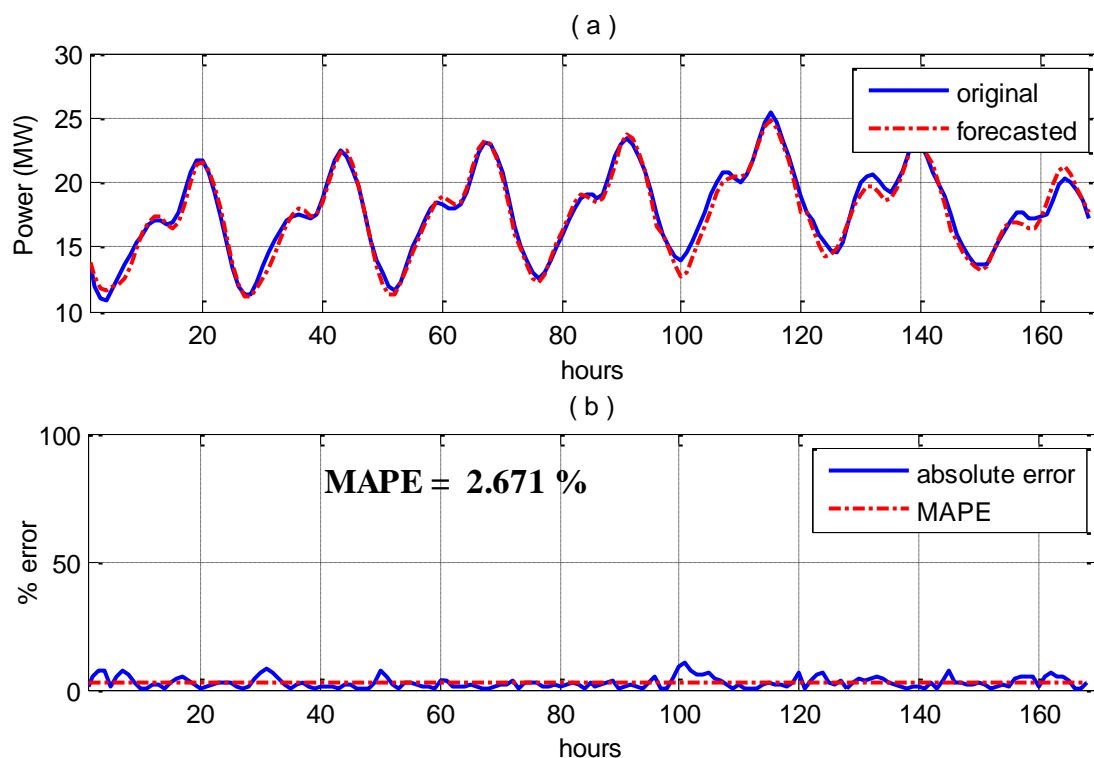


Figure 5.9: a) Actual and forecasted load for cold week period, SEC, 2005  
b) Absolute error and MAPE, next day, NN

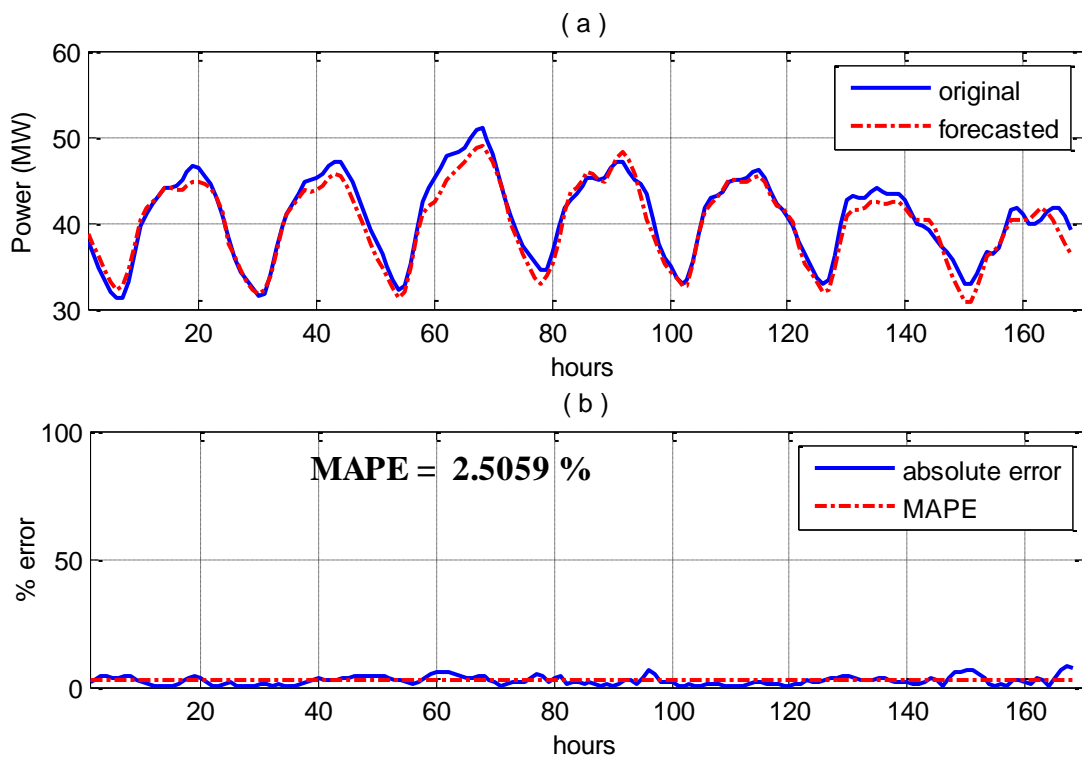


Figure 5.10: a) Actual and forecasted load for hot week period, SEC, 2005  
b) Absolute error and MAPE, next day, NN

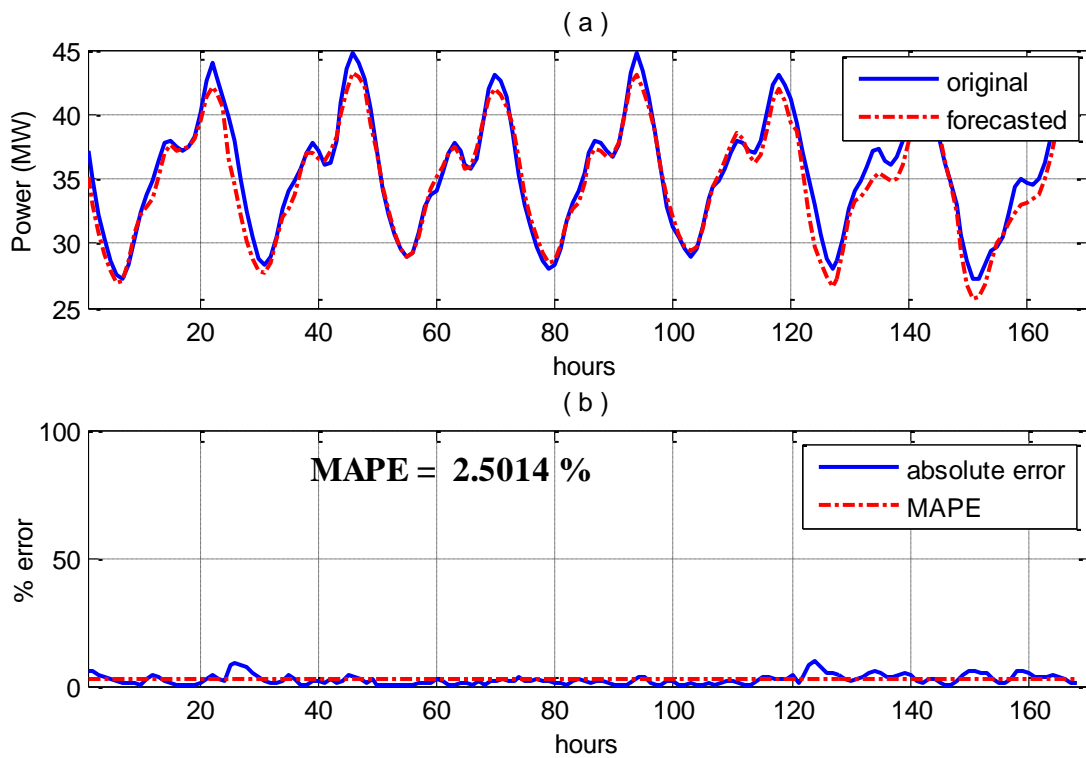


Figure 5.11: a) Actual and forecasted load for Ramadan season, SEC, 2005  
b) Absolute error and MAPE, next day, NN

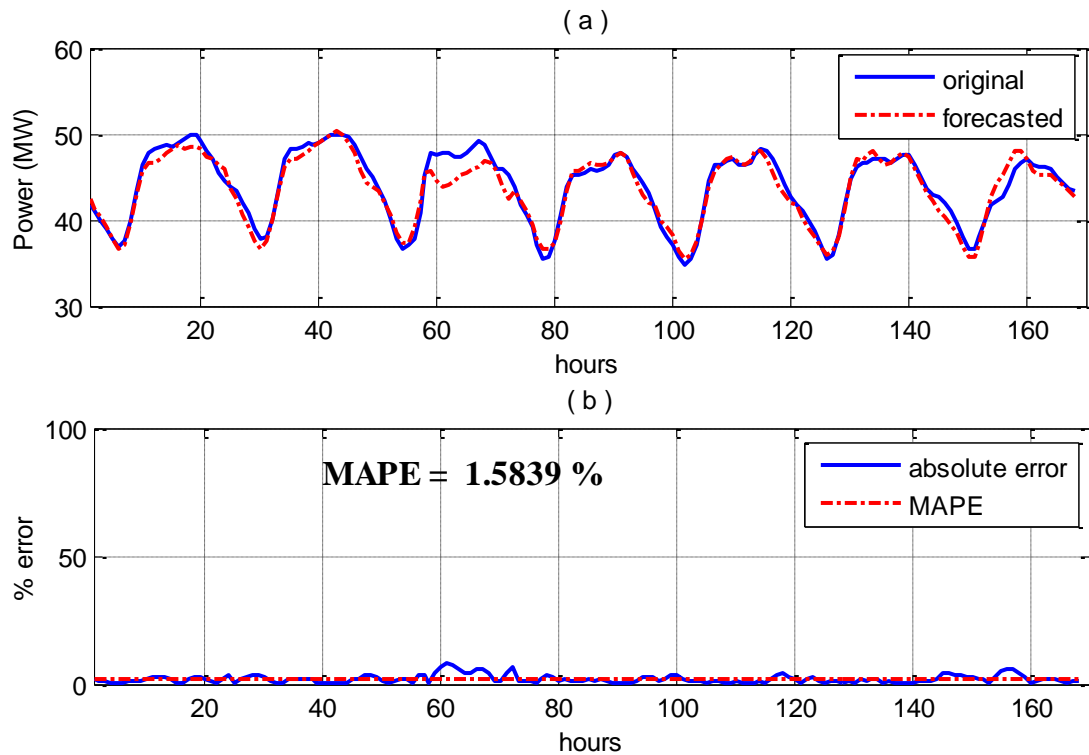


Figure 5.12: a) Actual and forecasted load for summer vacation season, SEC, 2005  
 b) Absolute error and MAPE, next day, NN

The performance of this model is satisfactory except for some few hours. This is because SEC data has many discontinuities in the data. Many days are missing and some of the days are omitted from the data because abnormality or data clipping. It is noted that the high error values appear in the discontinuity intervals. For example, 65 days are not available from year 2003 and 73 days from the forecasted year 2005 are missing. Some of these days are within same period and some of them are in different periods. Especially if these days are in the same interval, this will affect the historical load inputs data for the previous days to the forecasted day. Also, the error may be caused by a change in the load profile which is reflected to several possible reasons.

The most affecting factor in this situation is the sudden and unpredicted change of weather conditions like sand storm, rainfall or significant change in wind direction.

### 5.1.2.2 Hybrid Analytical Model Approach

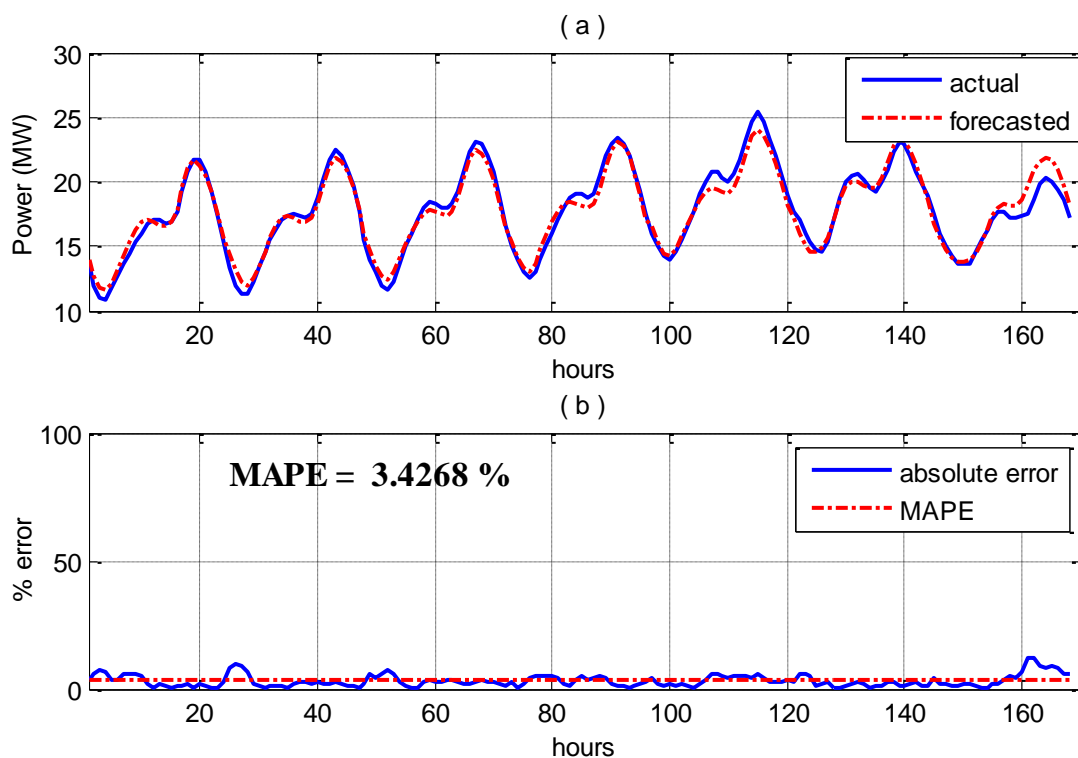


Figure 5.13: a) Actual and forecasted load for cold week period, SEC, 2005  
b) Absolute error and MAPE, next day, analytical model

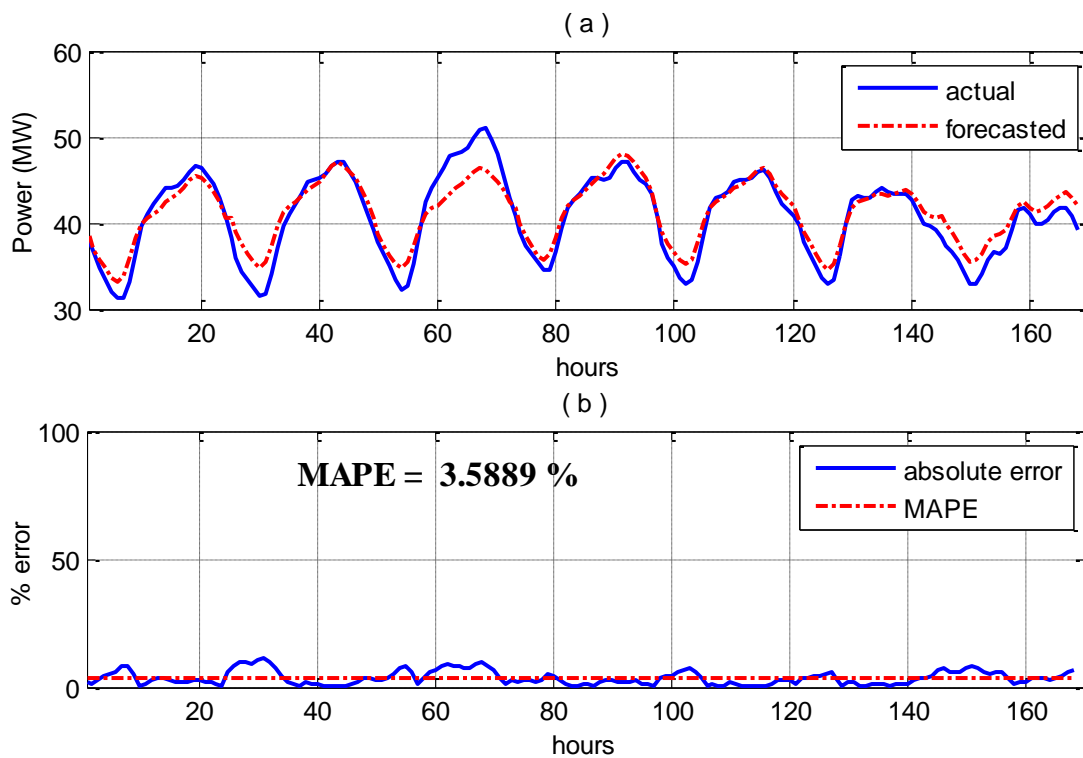


Figure 5.14: a) Actual and forecasted load for hot week period, SEC, 2005  
 b) Absolute error and MAPE, next day, analytical model

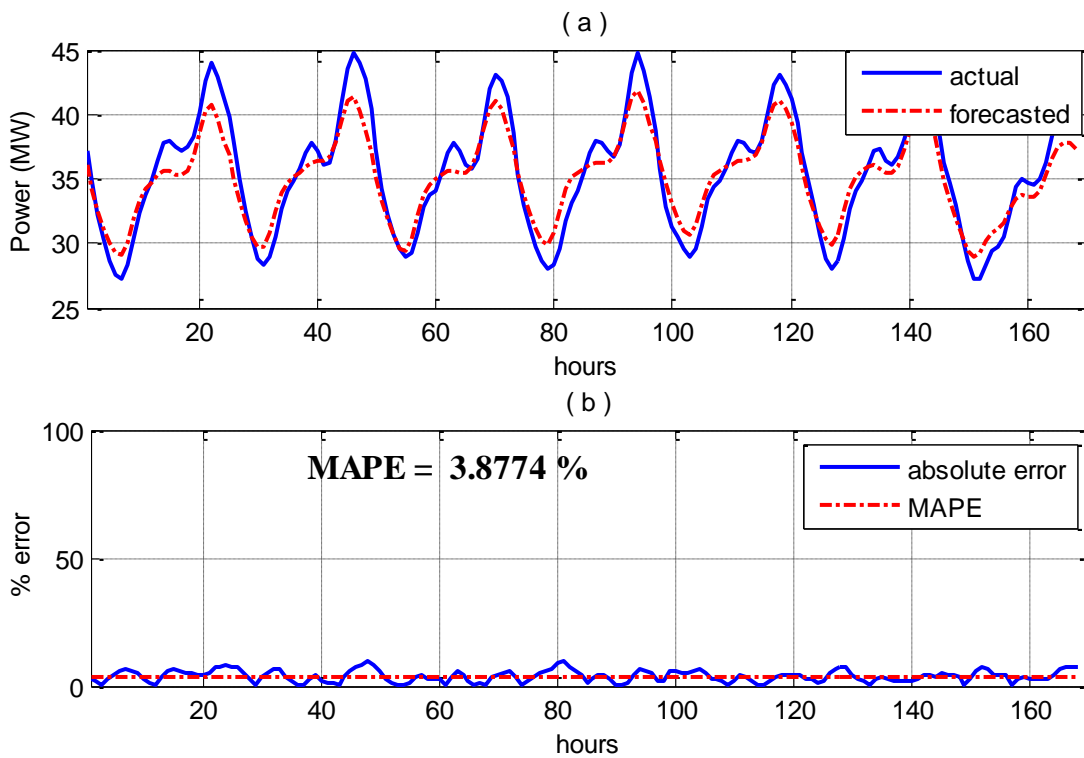


Figure 5.15: a) Actual and forecasted load for Ramadan season, SEC, 2005  
 b) Absolute error and MAPE, next day, analytical model



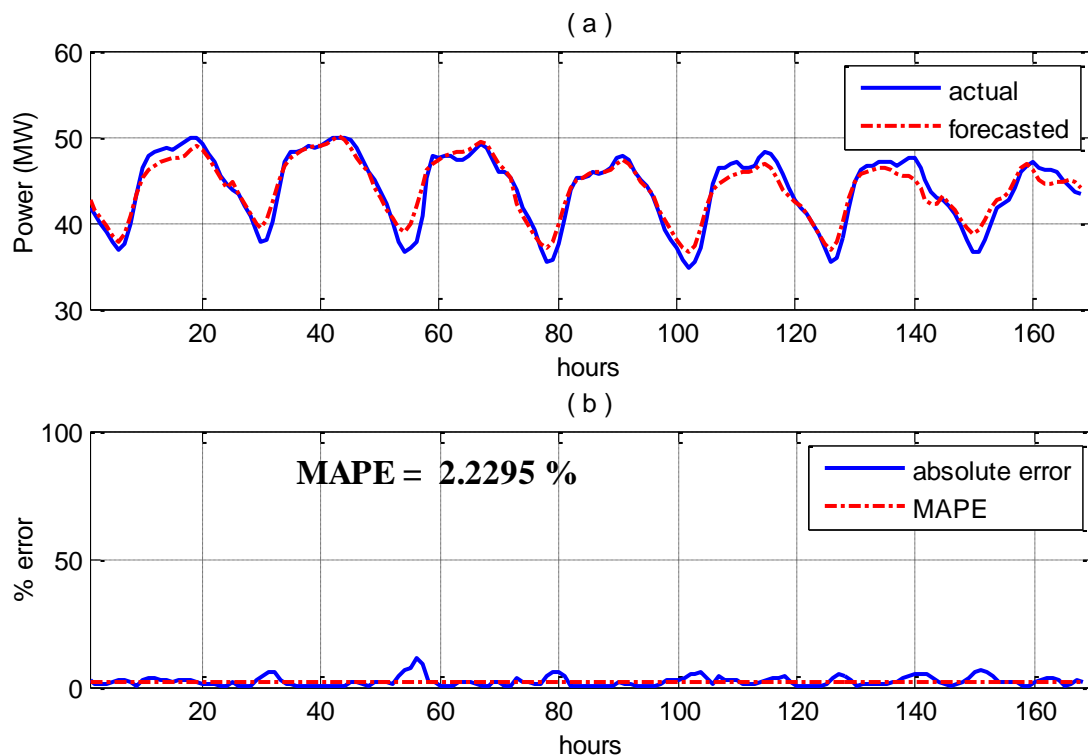


Figure 5.16: a) Actual and forecasted load for summer vacation season, SEC, 2005  
 b) Absolute error and MAPE, next day, analytical model

In hybrid analytical model, there are two main possible reasons for errors. This is due to forecasting two parameters which are daily shape behavior with zero mean value and next day average load consumption. In predicting daily load shape, some of the days may be transitional mode, meaning that they may be classified to a mode while they are belonging to other mode. This case is present, for example, in the intervals of seasons changing from winter to summer or vice versa. The shape does not change suddenly, but it changes gradually making it difficult to whether classify these days to winter mode or summer mode or even create a new mode called gradual change between winter and summer which is present in USA data. Moreover, within the same mode, there are some days that have abnormality in their shape for any reason like rainfall or sandstorm. Also, some days change the shape for unknown

reasons like a sudden occasion which could not be identified from either the academic calendar or the official calendar. As a result of that, people activities may be changed during these days and, consequently, the daily load shape is changing. After finding the average mode day, it is clear that these abnormal days are different in shape with their mode representative average day. The other factor is the error resulting from forecasting average power for next day using NN.

### **5.1.2.3 Iterative Forecasting Model**

Next day load forecasting model can be also modeled by repetitive use of the NN next hour models. This is achieved by forecasting the load of next hour at a time. After that, this load is aggregated to the series, so that the forecasts for the later hours will be based on the forecasts of the earlier ones. Next hour models are heavily dependent on recent hourly loads on the forecasting day. Since these load values are forecasted and not measured, forecasting errors are accumulating and the error values will increase accordingly. However, the error is not always increasing with the increase of the forecasted hours. This depends on the nature of data to be analyzed, inputs parameters and the forecasted hour. The model gives very accurate results when forecasting next 4 to 6 hours. There are some fluctuations of the error as clearly shown in figure 5.17 which displays the average MAPE for each number of forecasted hours over the entire evaluation year for SEC, Marafiq and USA data.

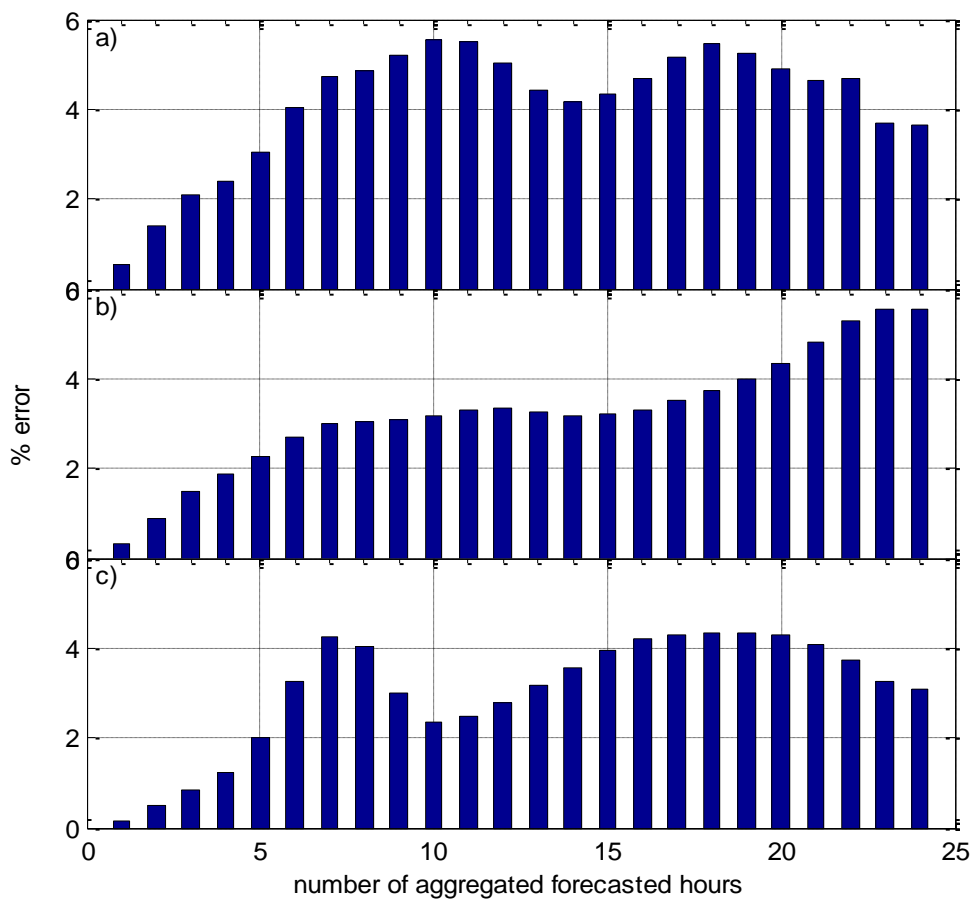


Figure 5.17: Average MAPE for each hour for: (a) SEC (b) Marafiq (c) USA data

For SEC data, the same forecasted periods using ANN and hybrid analytical models will be forecasted using the iterative model. The results are shown in figures 5.18 to 5.21.

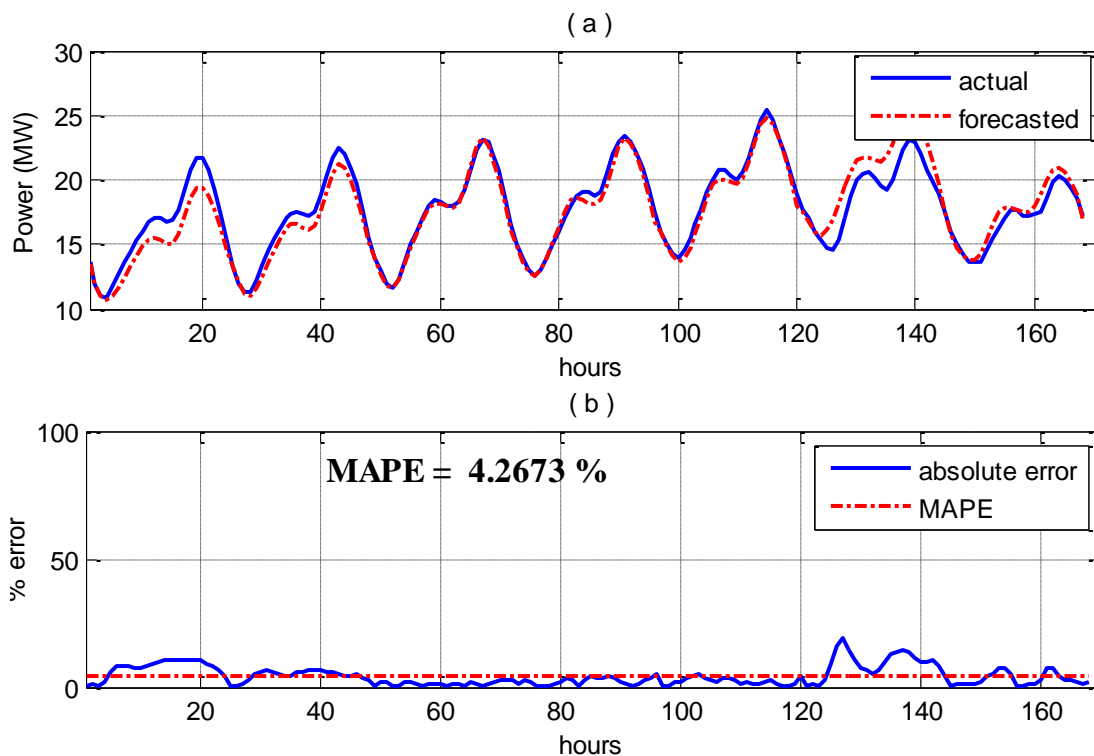


Figure 5.18: a) Actual and forecasted load for cold week period, SEC, 2005  
 b) Absolute error and MAPE, next day, iterative model

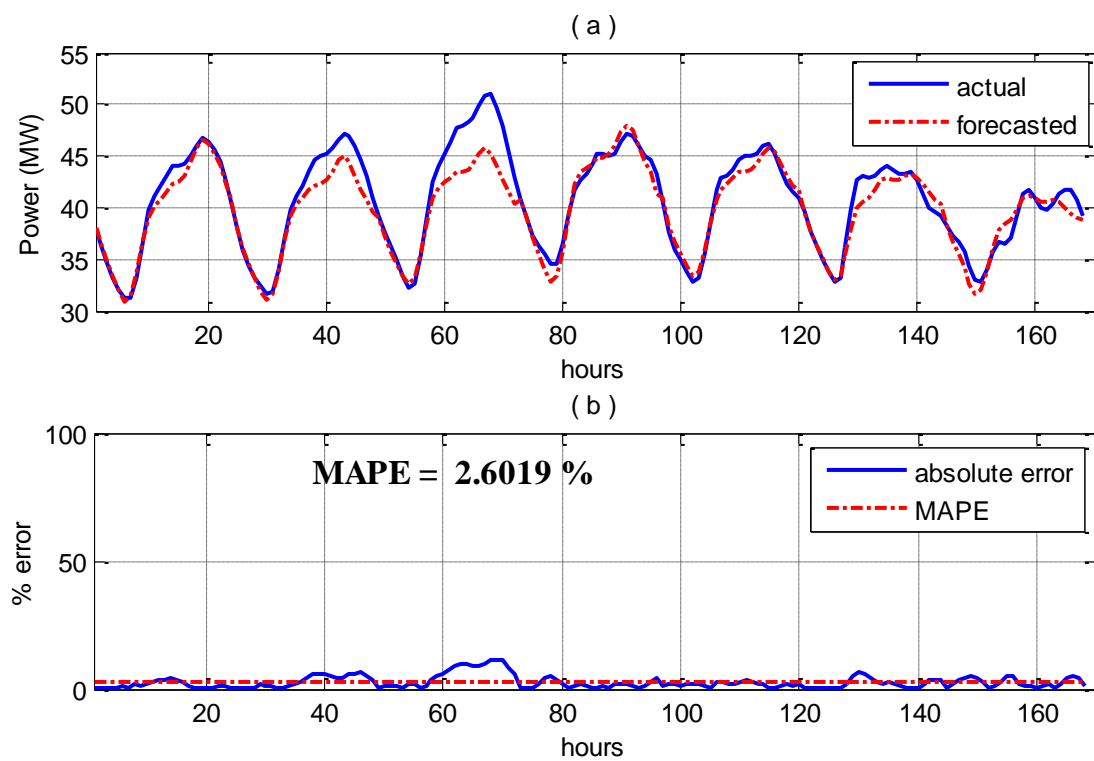


Figure 5.19: a) Actual and forecasted load for hot week period, SEC, 2005  
 b) Absolute error and MAPE, next day, iterative model

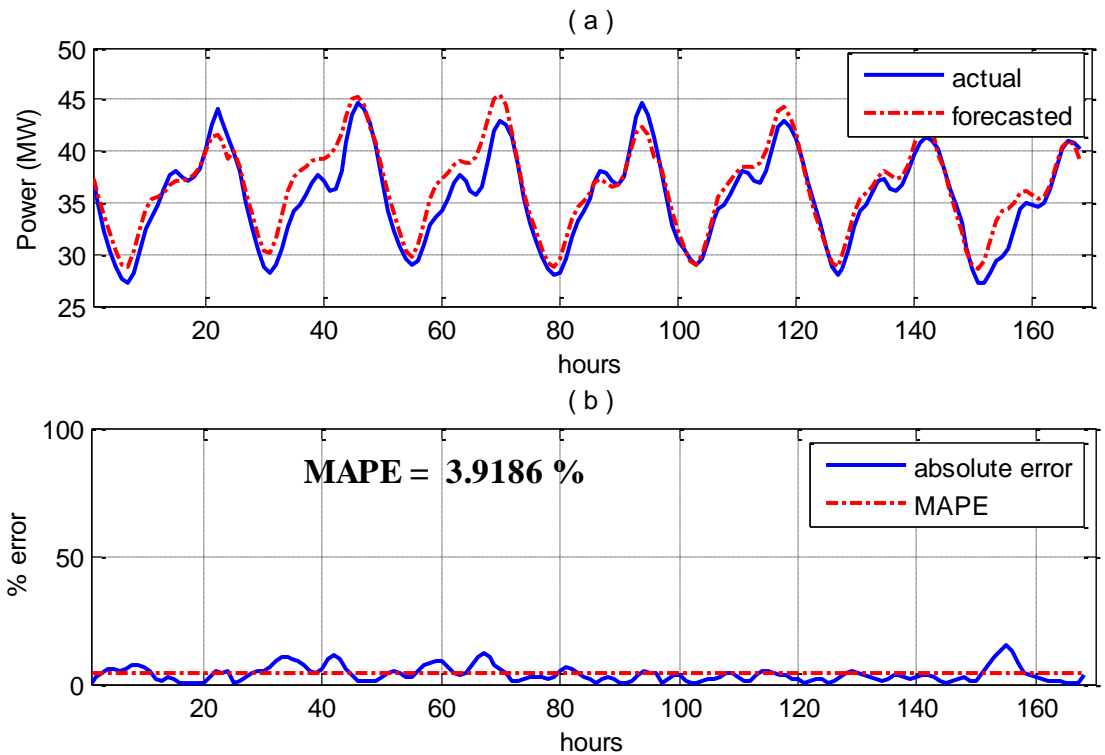


Figure 5.20: a) Actual and forecasted load for Ramadan season, SEC, 2005  
 b) Absolute error and MAPE, next day, iterative model

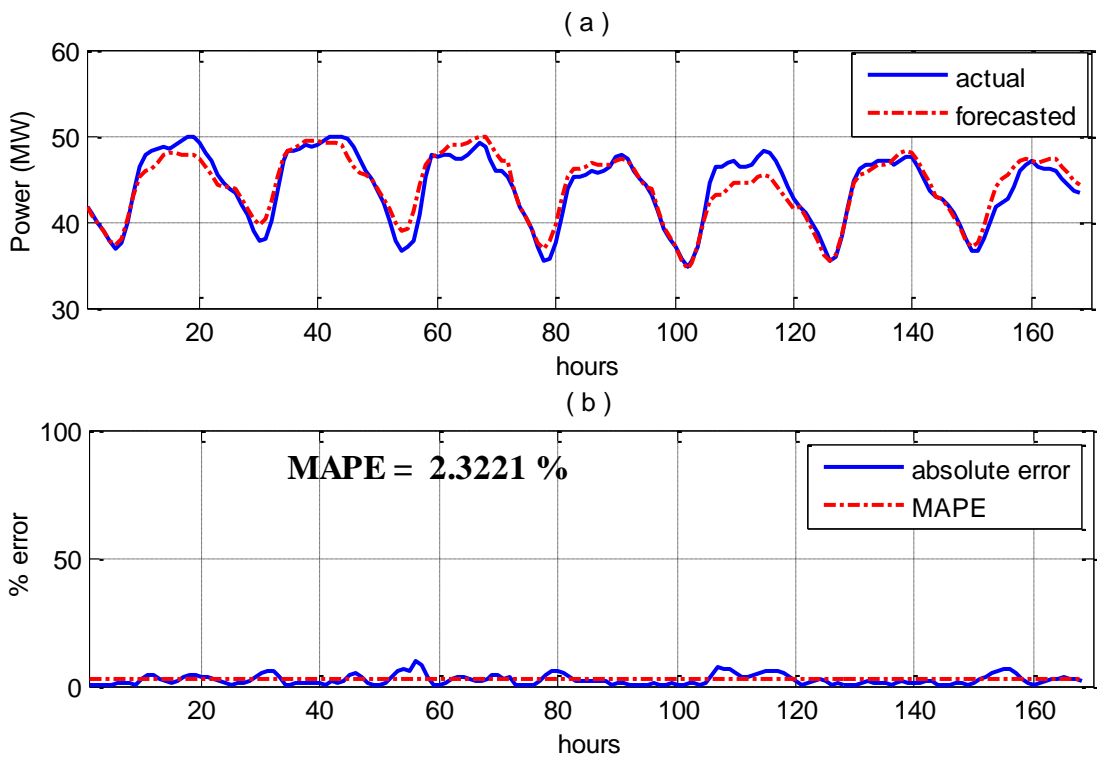


Figure 5.21: a) Actual and forecasted load for summer vacation season, SEC, 2005  
 b) Absolute error and MAPE, next day, iterative model

## 5.2 Marafiq Data

In this data source, the used data for training and model building are 2009 and 2010, while the forecasted period is up to 10 December 2011. As done in SEC data, typical four intervals selected from different seasons exposed to different characteristics will be shown. The typical selected dates for these seasons are shown in table 5.2.

Table 5.2: The selected dates to represent seasons for all models, Marafiq data

Season	Date	
	From	To
Winter	5/3/2011	11/3/2011
Summer	28/5/2011	3/6/2011
Ramadan	6/8/2011	12/8/2011
Summer Vacation	9/7/2011	15/7/2011

### 5.2.1 Next Hour Load Forecasting

#### 5.2.1.1 Neural Network Model Approach

Same approach used in SEC data will be used here. Comparisons of the ANN model output and the actual load and MAPE for the four intervals are shown in figures 5.22 to 5.25.

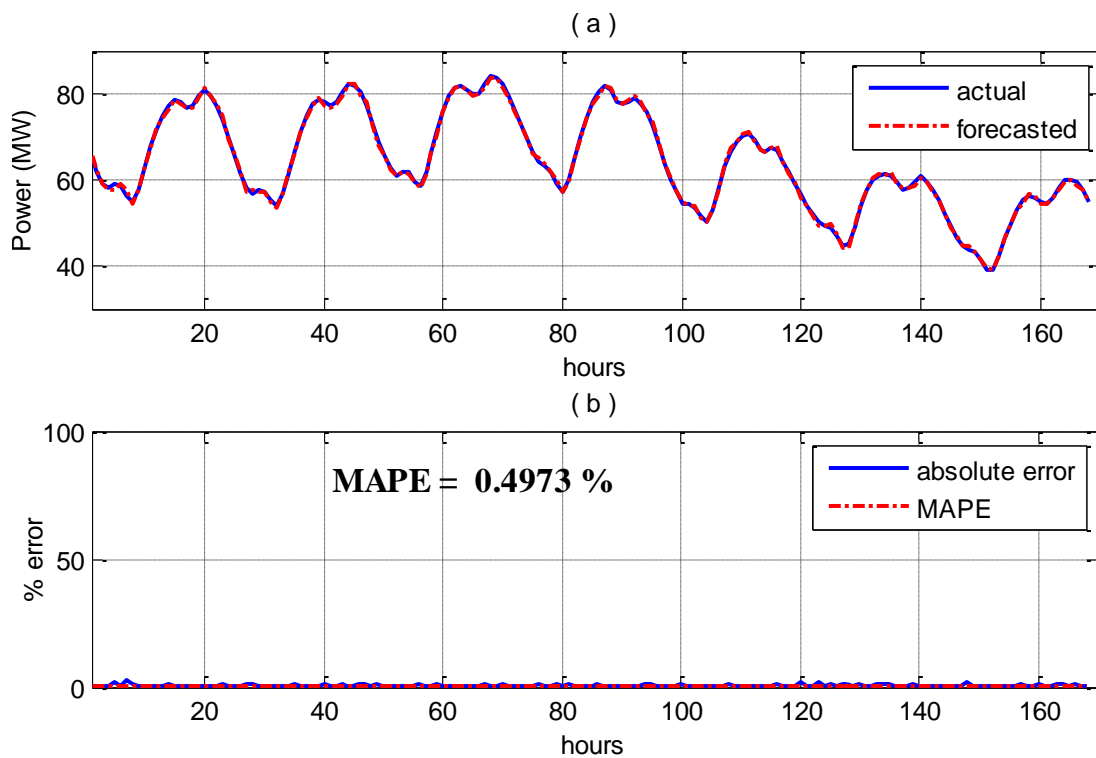


Figure 5.22: a) Actual and forecasted load for cold week period, Marafiq, 2011  
 b) Absolute error and MAPE, next hour, NN

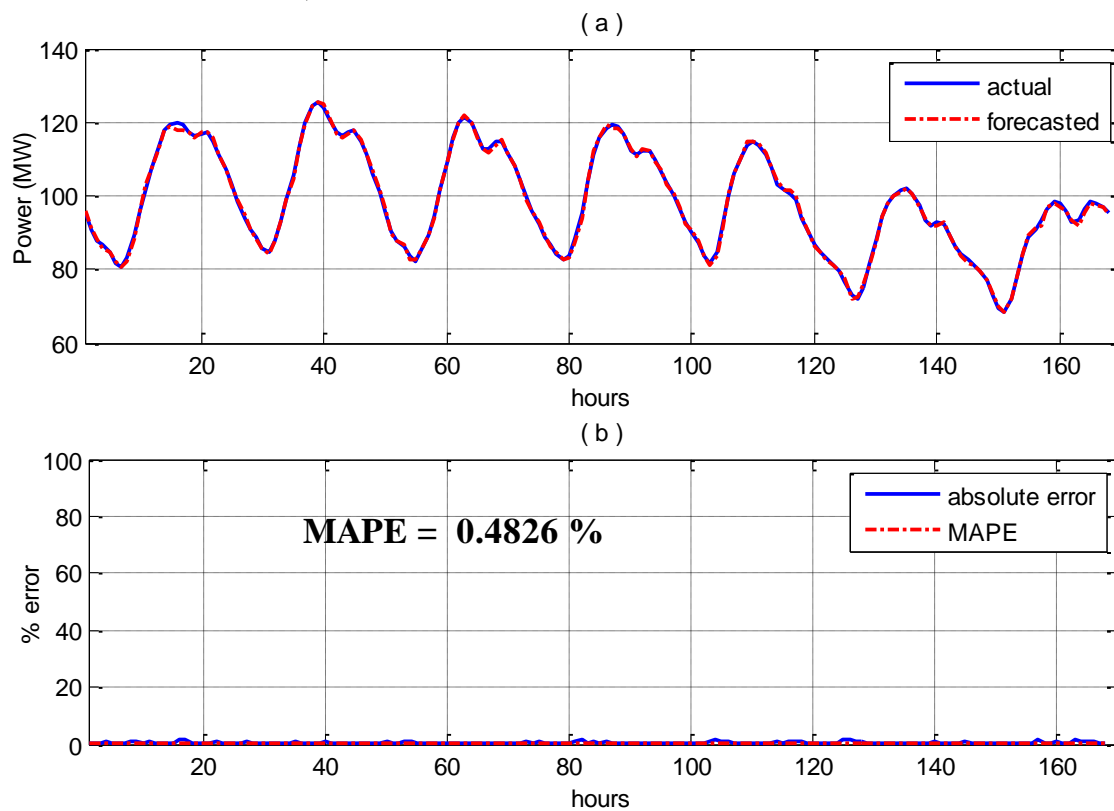


Figure 5.23: a) Actual and forecasted load for hot week period, Marafiq, 2011  
 b) Absolute error and MAPE, next hour, NN

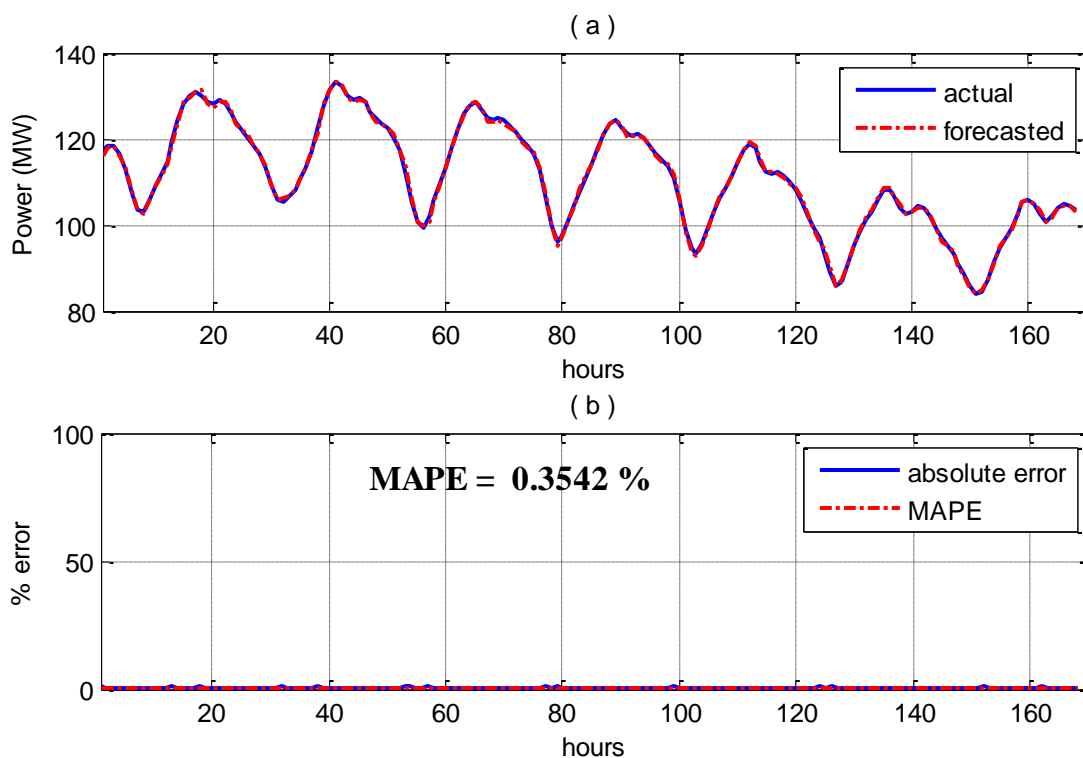


Figure 5.24: a) Actual and forecasted load for Ramadan season, Marafiq, 2011  
b) Absolute error and MAPE, next hour, NN

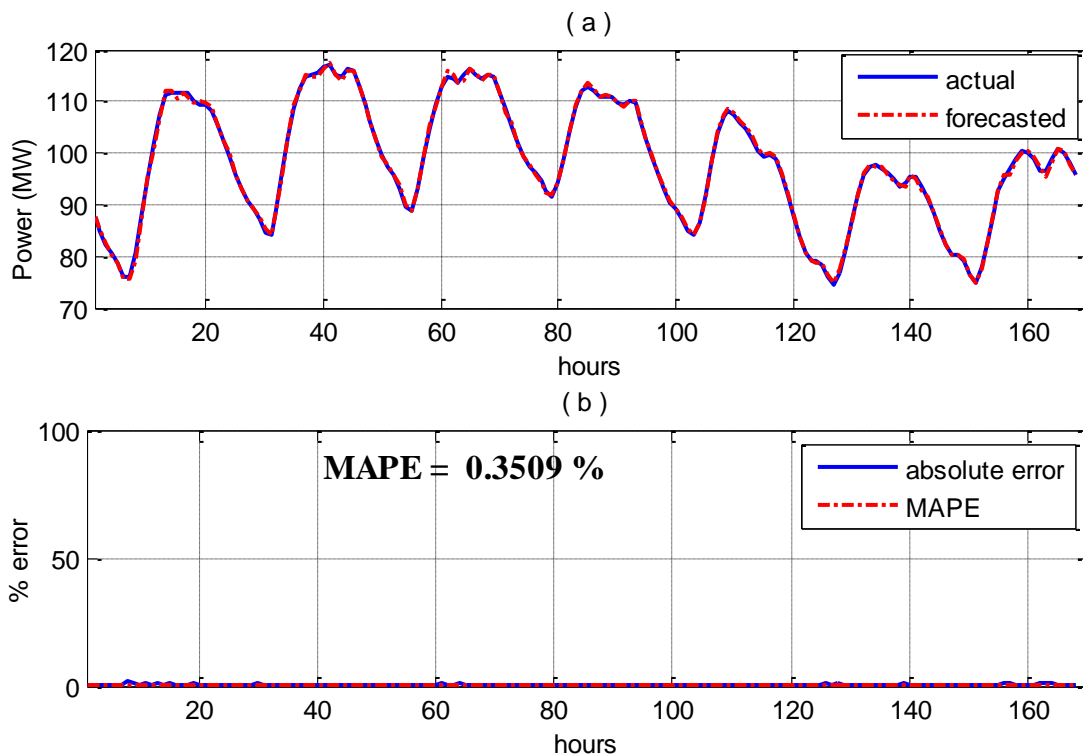


Figure 5.25: a) Actual and forecasted load for summer vacation season, Marafiq, 2011  
b) Absolute error and MAPE, next hour, NN



### 5.2.1.2 Hybrid Analytical Model Approach

Comparison between the hybrid analytical model output and the actual load, in addition to MAPE values for the four intervals are shown in figures 5.26 to 5.29.

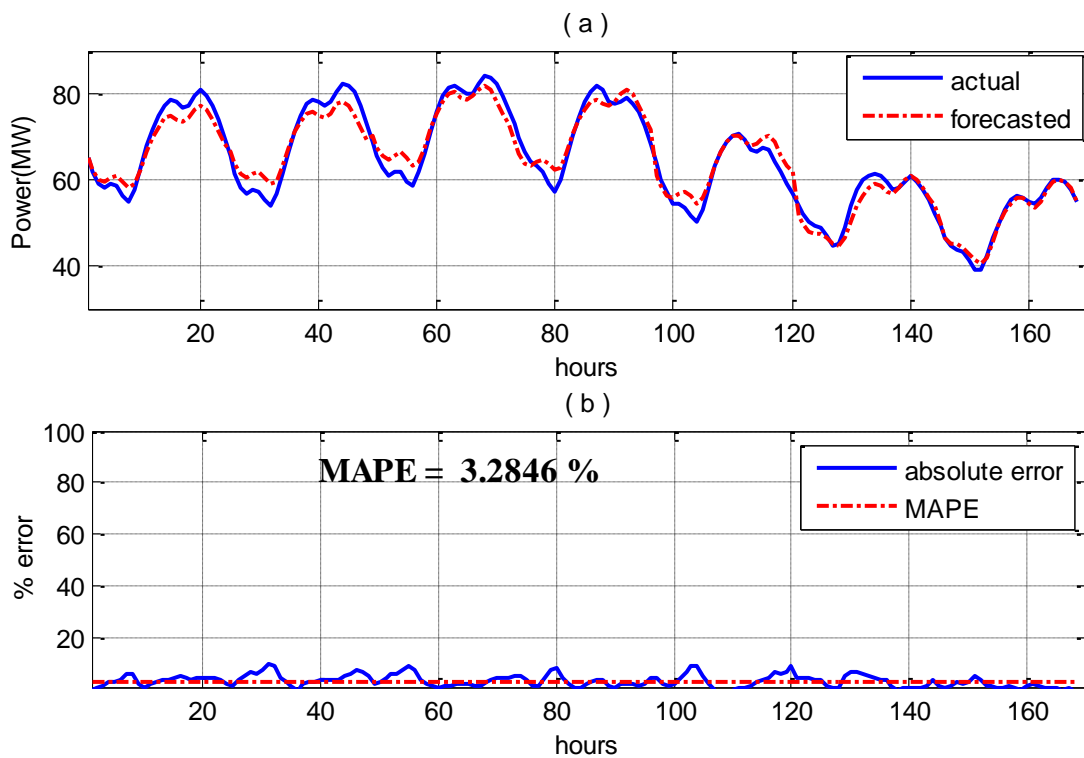


Figure 5.26: a) Actual and forecasted load for cold week period, Marafiq, 2011  
b) Absolute error and MAPE, next hour, analytical model

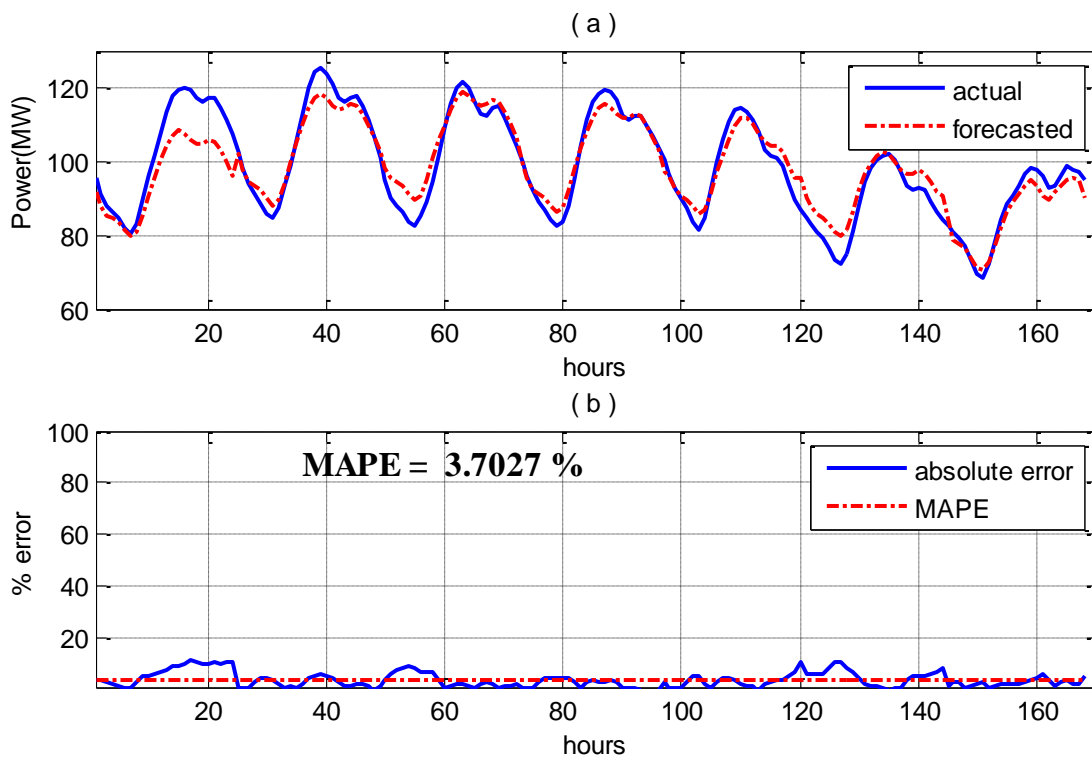


Figure 5.27: a) Actual and forecasted load for hot week period, Marafiq, 2011  
 b) Absolute error and MAPE, next hour, analytical model

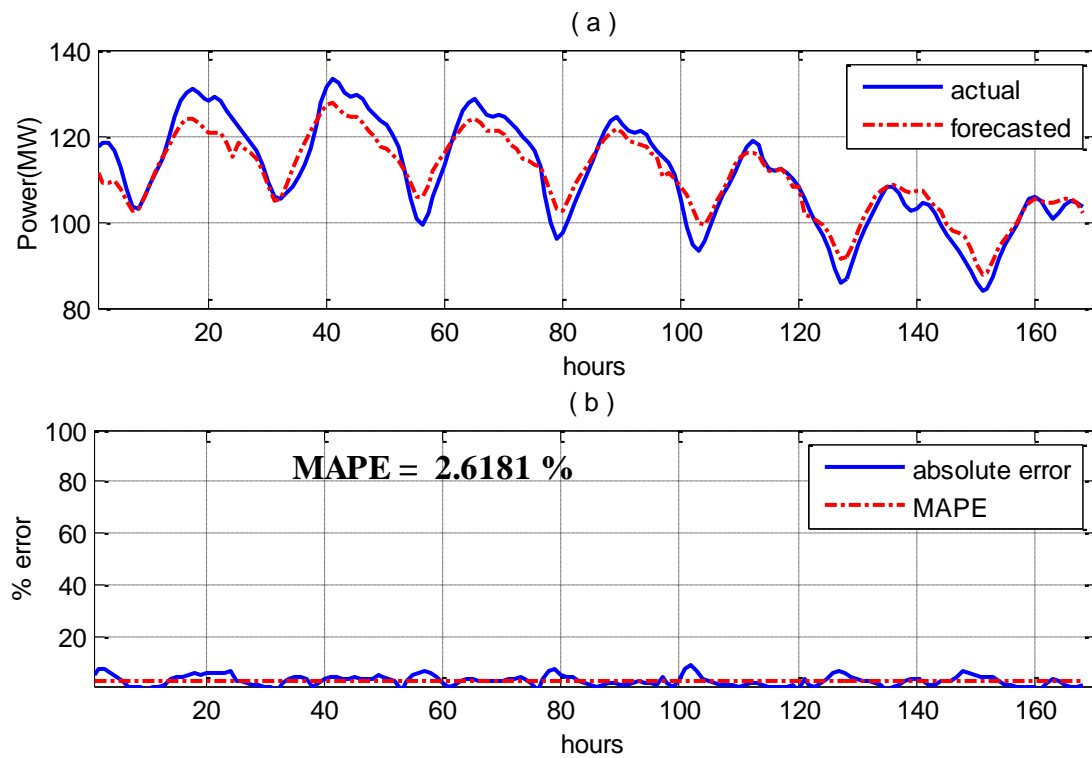


Figure 5.28: a) Actual and forecasted load for Ramadan season, Marafiq, 2011  
 b) Absolute error and MAPE, next hour, analytical model

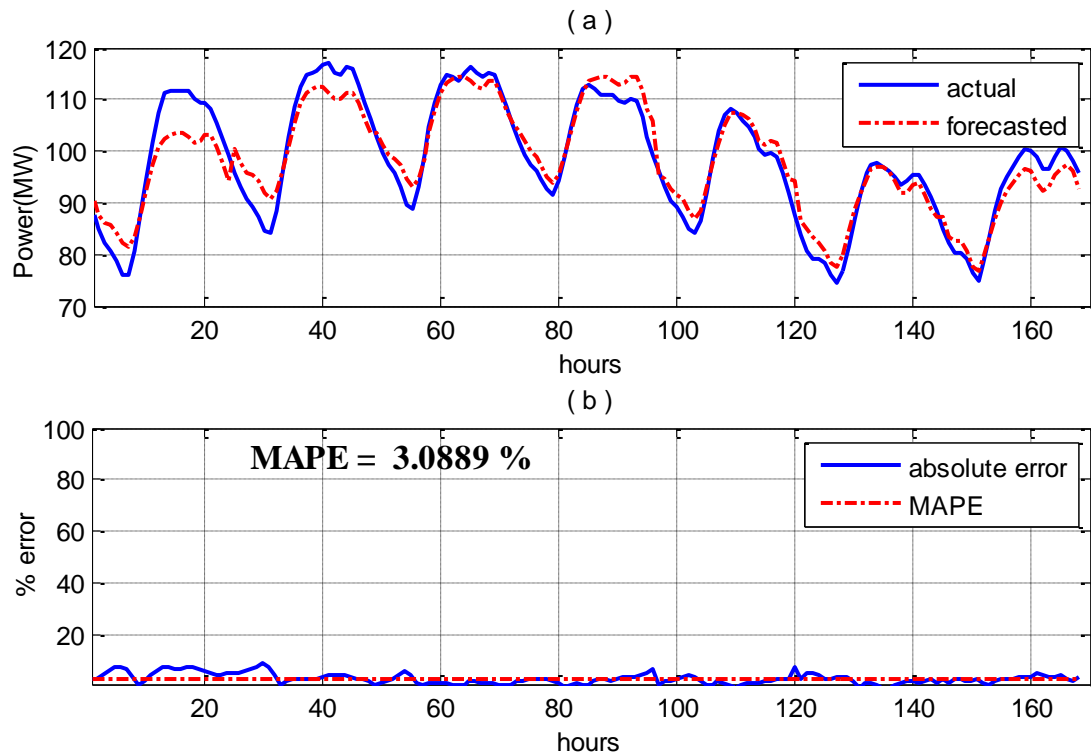


Figure 5.29: a) Actual and forecasted load for summer vacation season, Marafiq, 2011  
 b) Absolute error and MAPE, next hour, analytical model

As in ANN next hour load forecasting model for SEC data, accurate results are obtained where MAPE values are ranging between 0.3509 % and 0.4973 % and hence the model is accurately satisfying next hour forecasting for both SEC and Marafiq data. As expected, ANN model forecasts next hour load in better performance than hybrid analytical model. Table 5.3 summarizes all MAPE values for the two models for each set of data.

Table 5.3: Summary of MAPE results of next hour models for SEC and Marafiq data

		SEC	Marafiq
Winter Period	ANN	0.9357 %	0.4973 %
	Hybrid	3.4268 %	3.2846 %
Hot Period	ANN	0.6084 %	0.4826 %
	Hybrid	3.5889 %	3.7027 %
Ramadan Period	ANN	0.7881 %	0.3542 %
	Hybrid	3.8774 %	2.6181 %
Summer Period	ANN	0.6517 %	0.3509 %
	Hybrid	2.2295 %	3.0889 %

## 5.2.2 Next Day Load Forecasting

### 5.2.2.1 Neural Network Model Approach

Comparison between the ANN model output and the actual load, in addition to MAPE values for the four intervals are shown in figures 5.30 to 5.33.

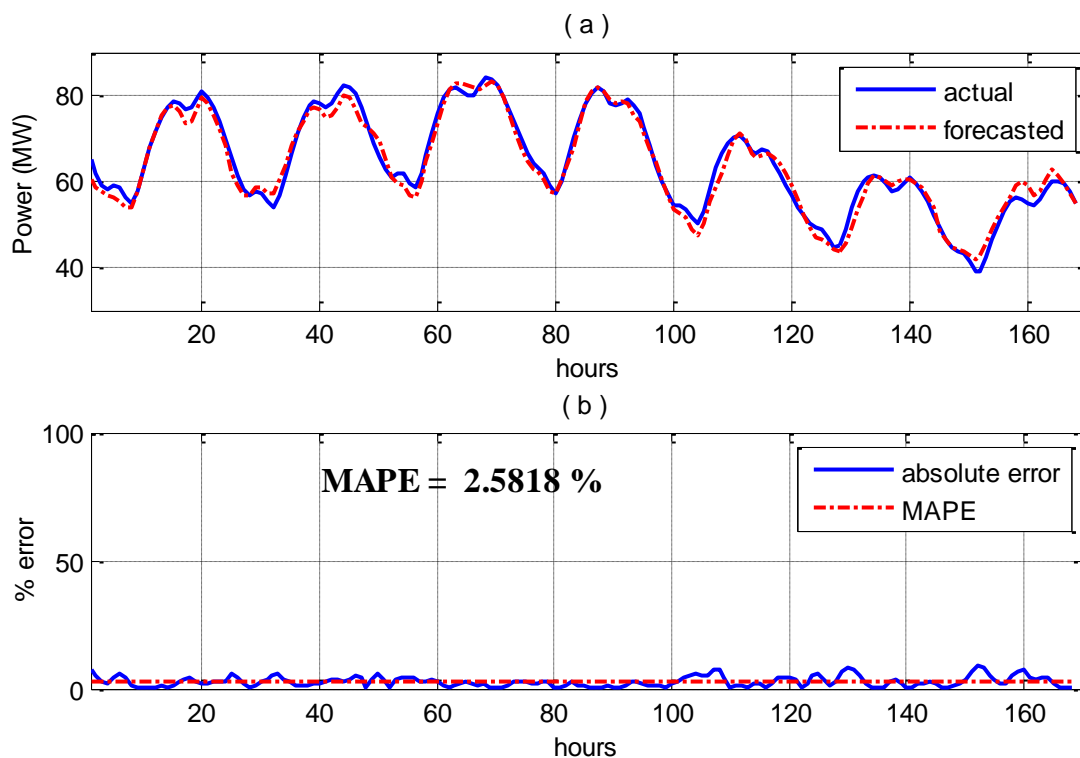


Figure 5.30: a) Actual and forecasted load for cold week period, Marafiq, 2011  
b) Absolute error and MAPE, next day, NN

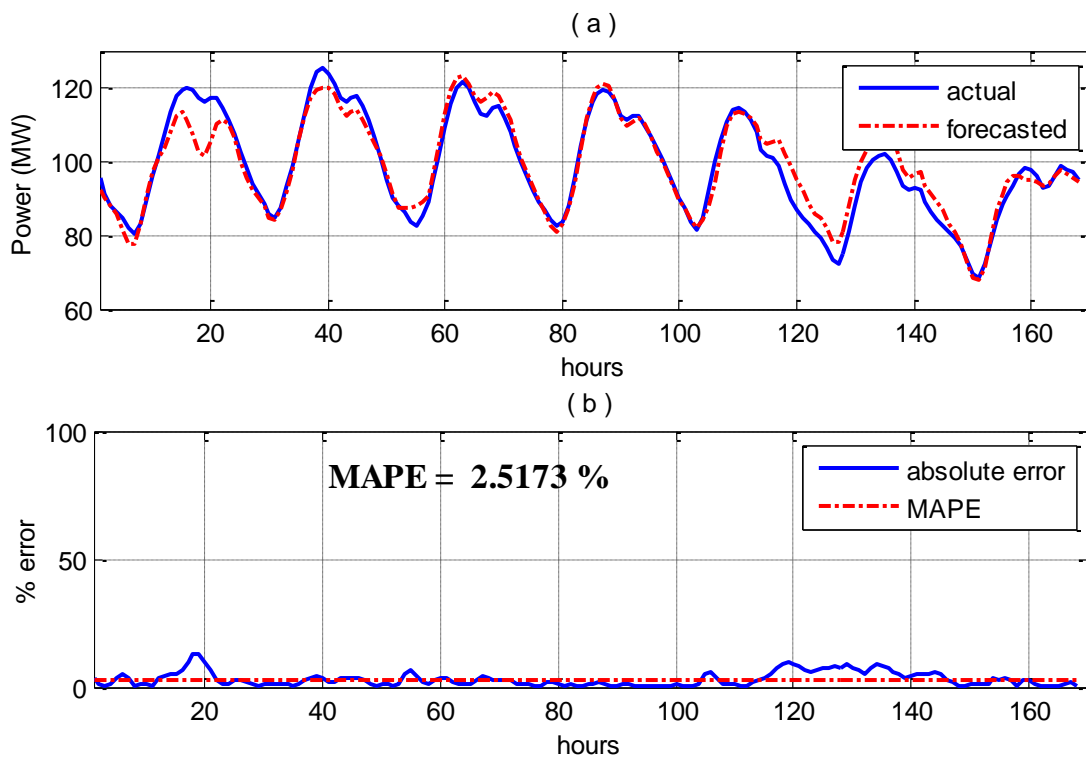


Figure 5.31: a) Actual and forecasted load for hot week period, Marafiq, 2011  
 b) Absolute error and MAPE, next day, NN

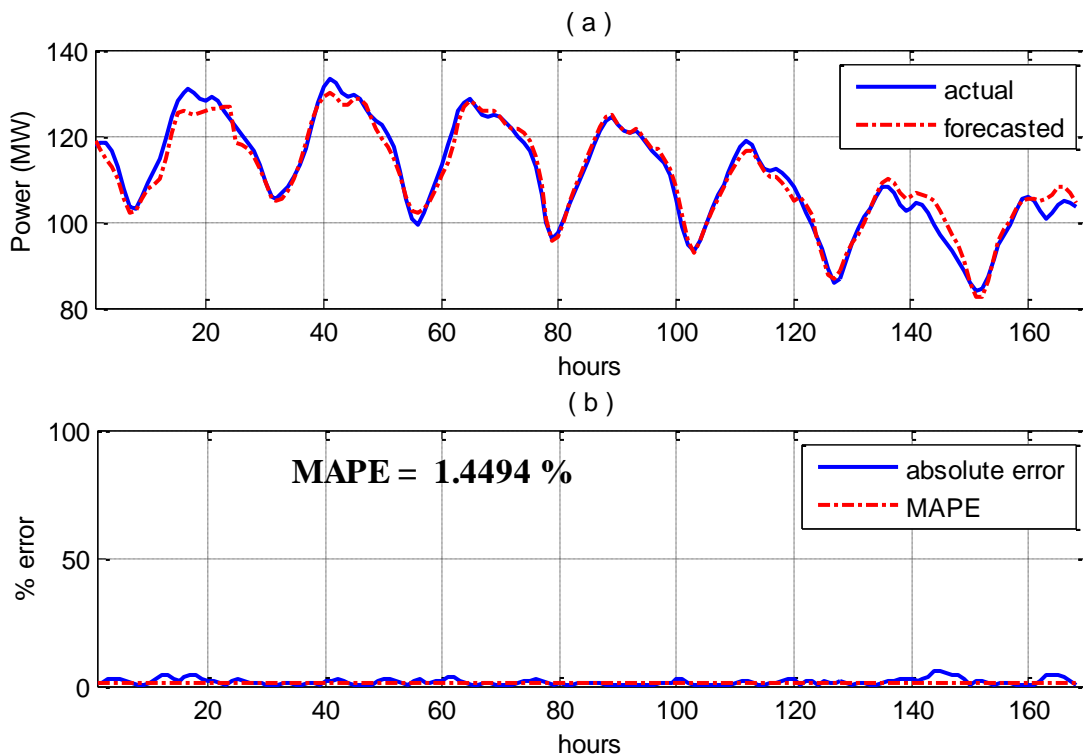


Figure 5.32: a) Actual and forecasted load for Ramadan season, Marafiq, 2011  
 b) Absolute error and MAPE, next day, NN

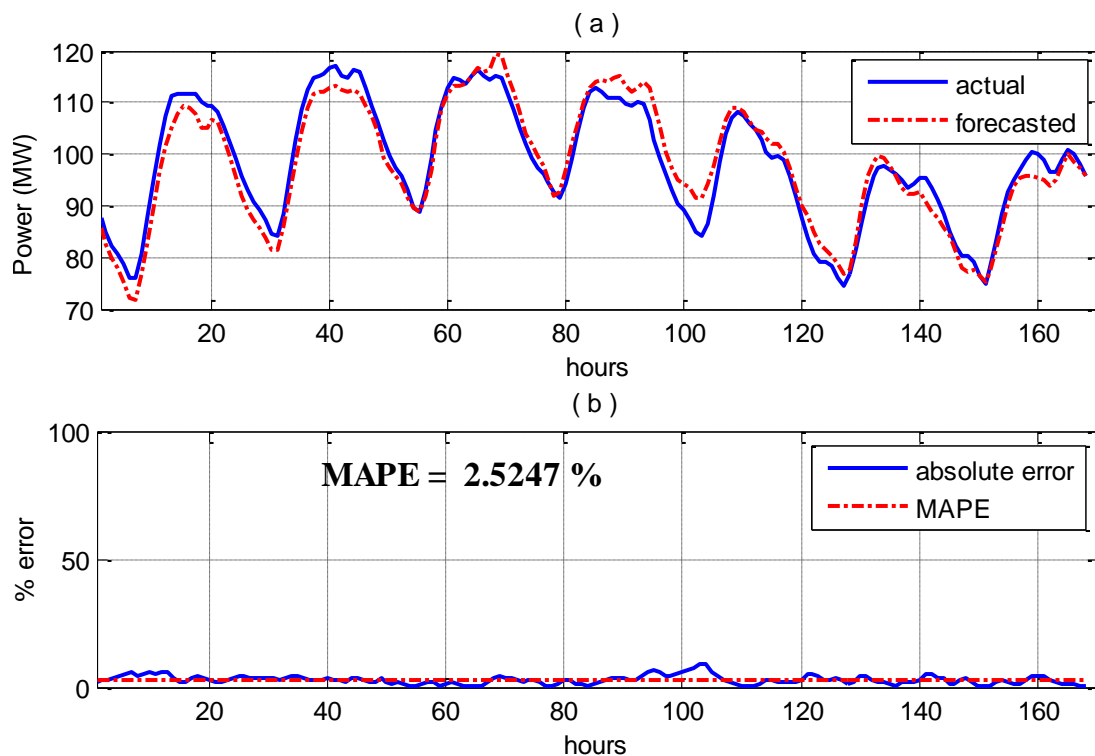


Figure 5.33: a) Actual and forecasted load for summer vacation season, Marafiq, 2011  
 b) Absolute error and MAPE, next day, NN

Since Marafiq data are complete, consistent and organized, the obtained results from this model is very satisfactory and ranging within good limits. MAPE values for the four typical intervals are between 1.4494 % and 2.5818 % which shows a good indication for model validity.

### 5.2.2.2 Hybrid Analytical Model Approach

Figures 5.34 to 5.37 show a comparison between the hybrid analytical model output and the actual load, in addition to MAPE values for the four intervals.

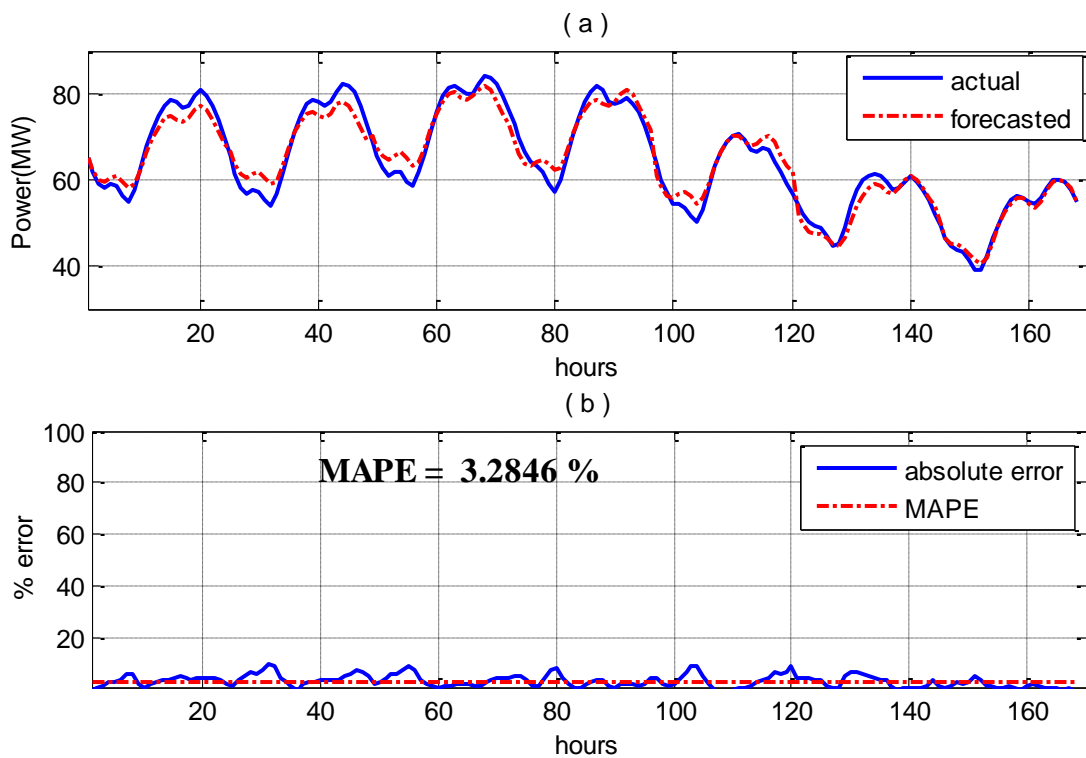


Figure 5.34: a) Actual and forecasted load for cold week period, Marafiq, 2011  
 b) Absolute error and MAPE, next day, analytical model

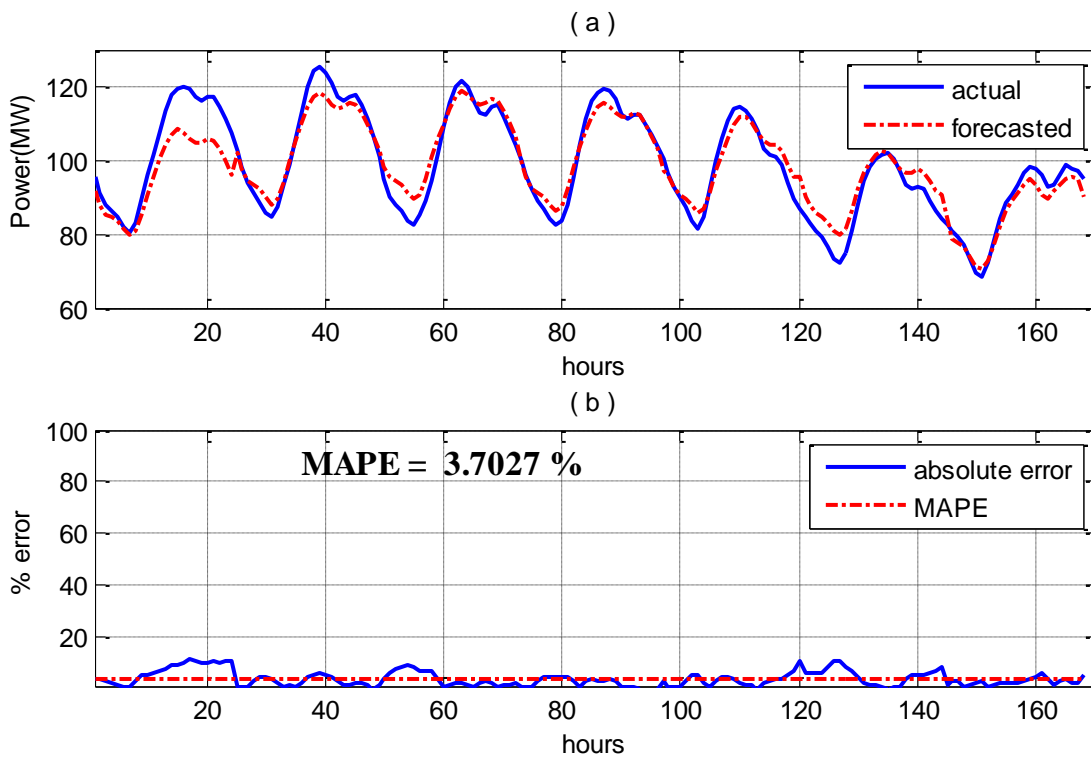


Figure 5.35: a) Actual and forecasted load for hot week period, Marafiq, 2011  
 b) Absolute error and MAPE, next day, analytical model

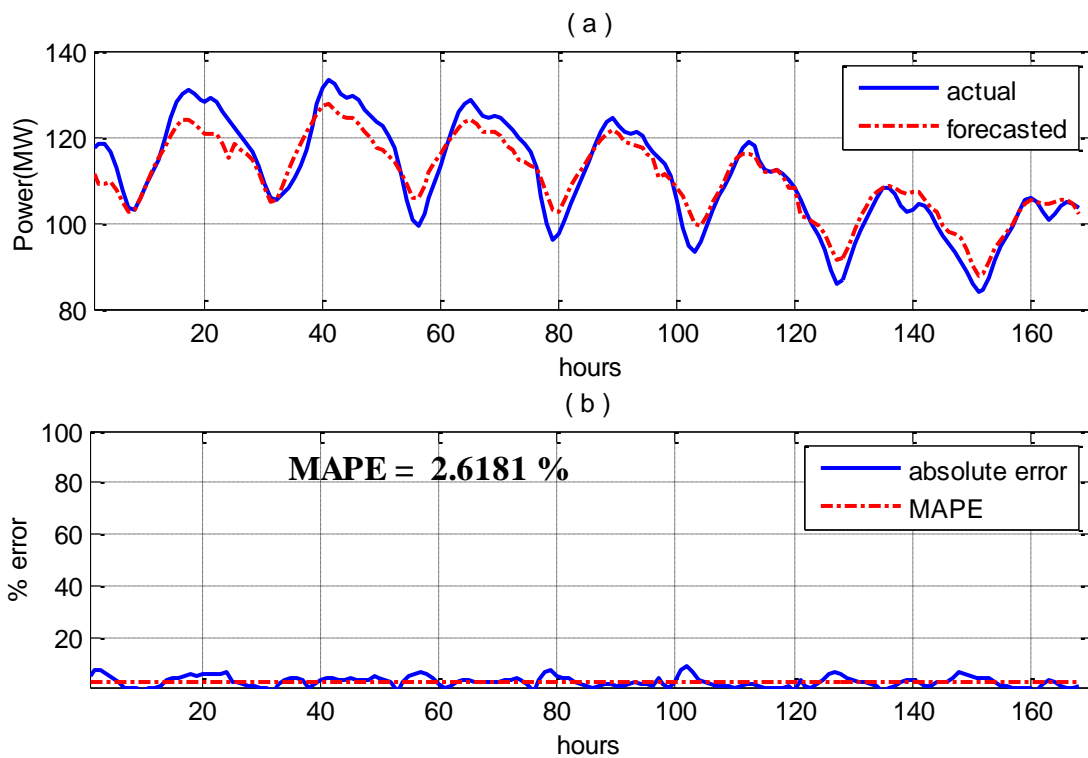


Figure 5.36: a) Actual and forecasted load for Ramadan season, Marafiq, 2011  
 b) Absolute error and MAPE, next day, analytical model

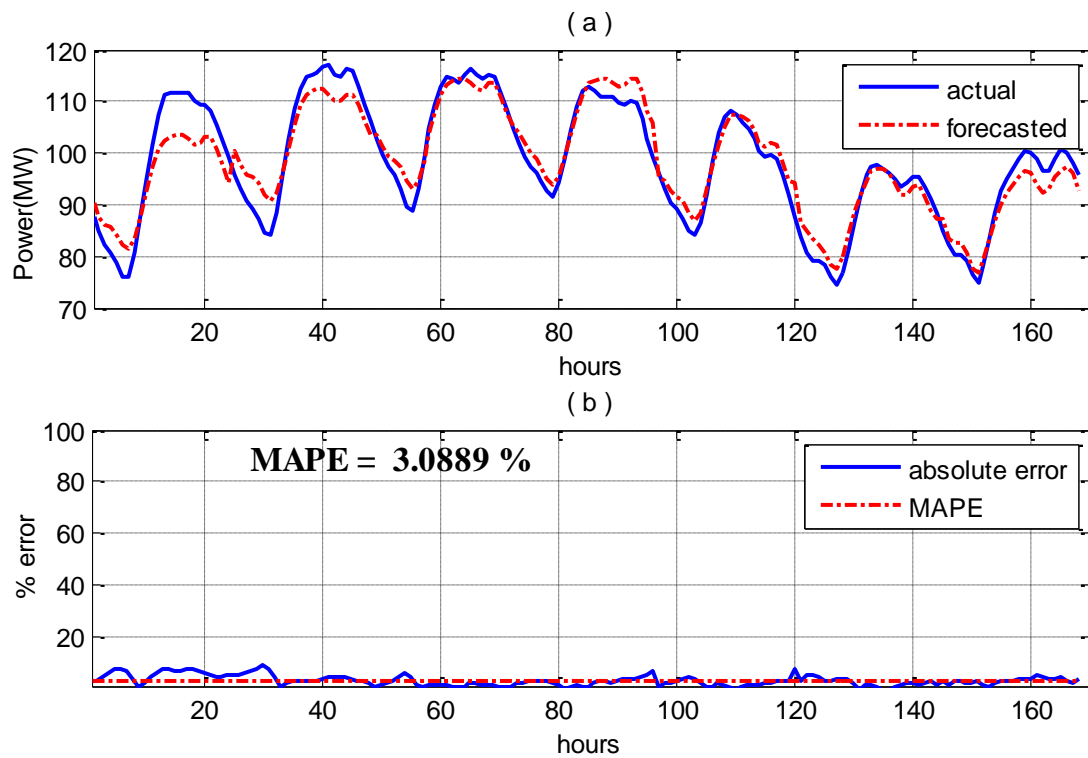


Figure 5.37: a) Actual and forecasted load for summer vacation season, Marafiq, 2011  
 b) Absolute error and MAPE, next day, analytical model



Same reasons for errors mentioned in SEC data analysis can be considered in Marafiq data. This model shows also satisfactory results and the MAPE values are ranging between 2.6181 % and 3.7027 % and this is an indication of the validity of the hybrid analytical model.

### 5.2.2.3 Iterative Forecasting Model

The same forecasted periods using ANN and hybrid analytical models will be forecasted using the iterative model. The results are shown in figures 5.38 to 5.41.

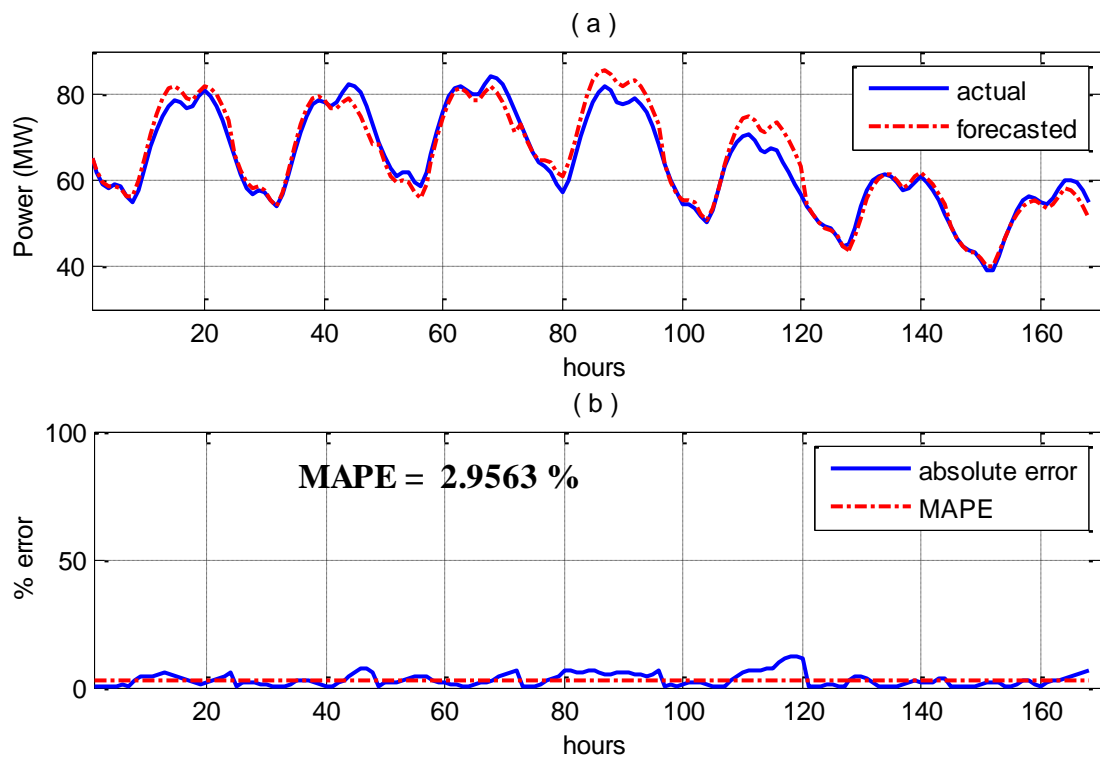


Figure 5.38: a) Actual and forecasted load for cold week period, Marafiq, 2011  
b) Absolute error and MAPE, next day, iterative model

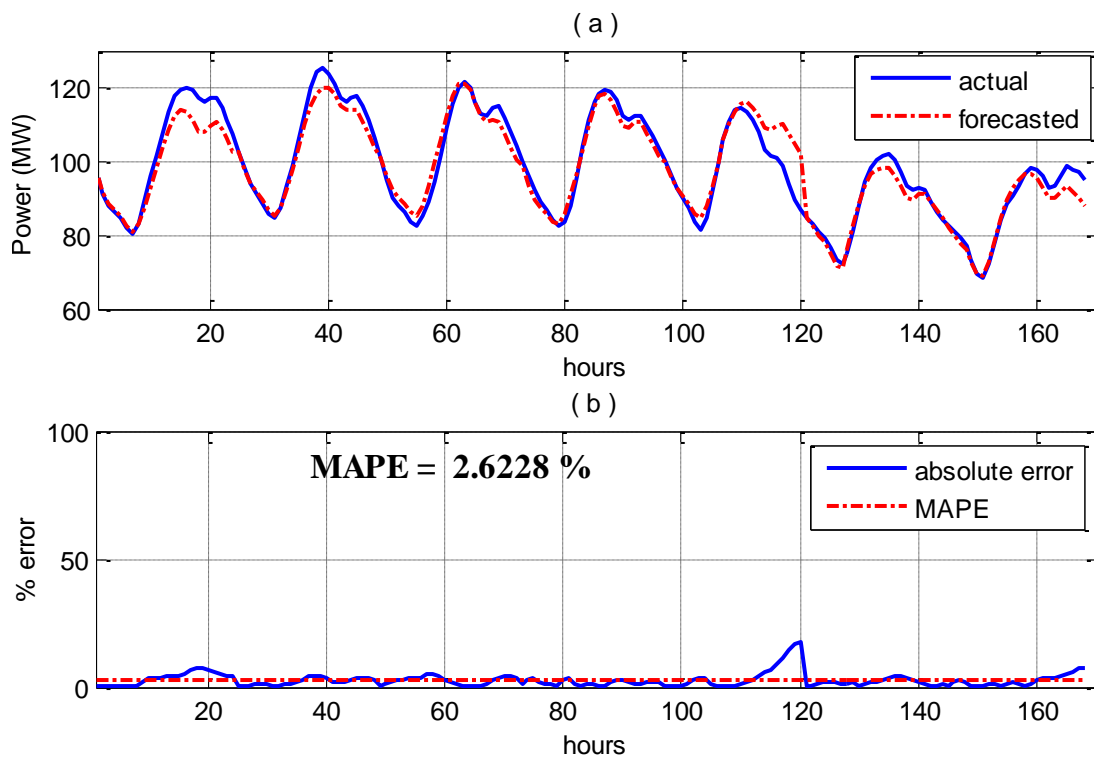


Figure 5.39: a) Actual and forecasted load for hot week period, Marafiq, 2011  
 b) Absolute error and MAPE, next day, iterative model

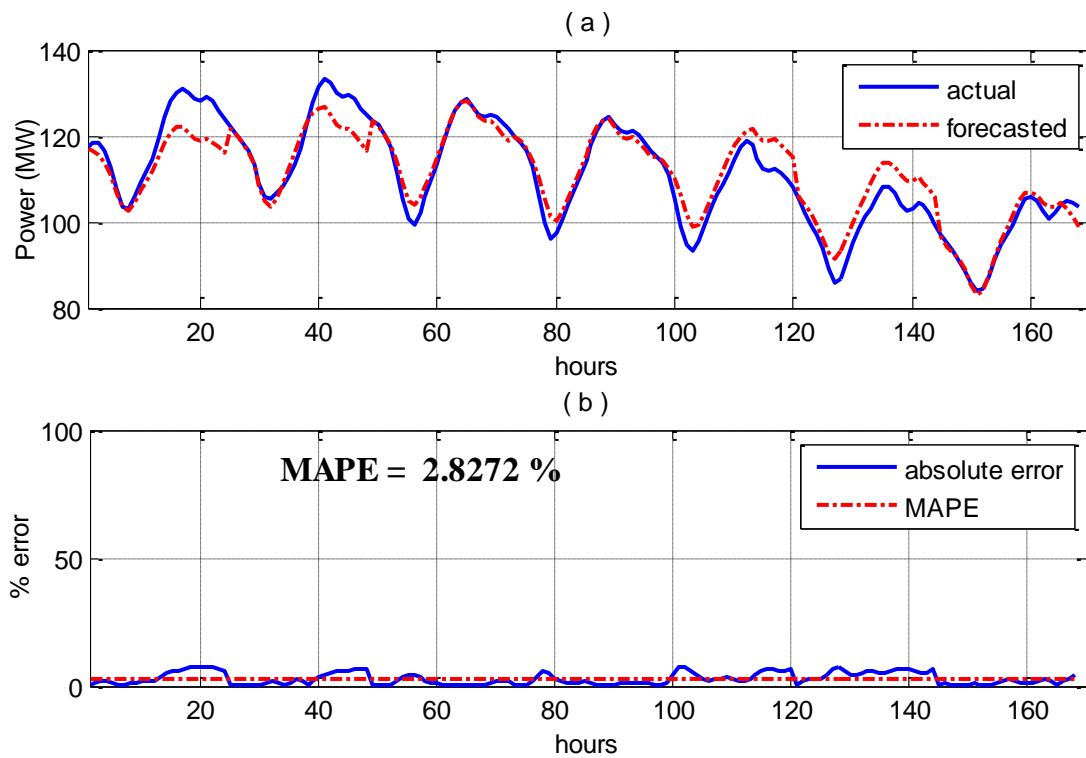


Figure 5.40: a) Actual and forecasted load for Ramadan season, Marafiq, 2011  
 b) Absolute error and MAPE, next day, iterative model

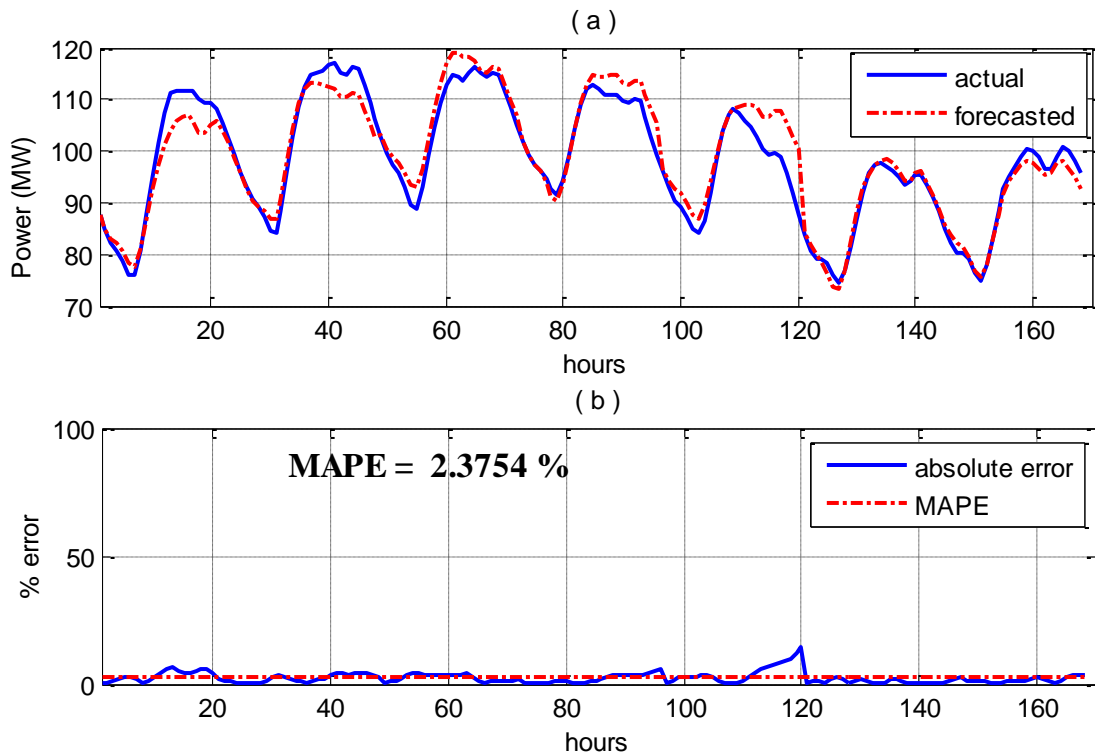


Figure 5.41: a) Actual and forecasted load for summer vacation season, Marafiq, 2011  
 b) Absolute error and MAPE, next day, iterative model

Therefore, forecasting next day load using iterative model achieved good results. With the exception of few hours where MAPE values are relatively high, the results show the effectiveness of this model especially when trying to forecast next 10 to 12 hours.

To compare between the results of the three approaches for both data sources, it is noted that all models give reasonable results except for few hours which are not comparable with several good results. Actually, there is no much difference for MAPE values of all models. Table 5.4 shows MAPE results obtained from each model for the two sources of data.

Table 5.4: Summary of MAPE results of next day models for SEC and Marafiq data

		SEC	Marafiq
Winter Week Period	NN	2.671 %	2.5818 %
	iterative	4.2673 %	2.9563 %
	Hybrid	3.4268 %	3.2846 %
Hot Week Period	NN	2.5059 %	2.5173 %
	iterative	2.6019 %	2.6228 %
	Hybrid	3.5889 %	3.7027 %
Ramadan Week Period	NN	2.5014 %	1.4494 %
	iterative	3.9186 %	2.8272 %
	Hybrid	3.8774 %	2.6181 %
Summer Week Period	NN	1.5839 %	2.5247 %
	iterative	2.3221 %	2.3754 %
	Hybrid	2.2295 %	3.0889 %

### 5.3 Summary and Conclusions of the Chapter

- This chapter shows the results of all models for SEC data and Marafiq data.
- For each set of data, the proposed models are next hour and next day load forecasting using ANN and Hybrid analytical models.
- Typical intervals exposed to different weather conditions and people activities are selected to check the validity of all models.
- Results show accurate performance using ANN and reasonable results using hybrid analytical model for next hour load forecasting for both data sources.
- For next day load forecasting using ANN and Hybrid analytical model, the results are in reasonable and satisfactory level except for some few points.
- Iterative forecasting model is used to forecast next day load to compare the results with other models and to show the validity and effectiveness of all proposed models

## **CHAPTER 6**

# **MODELS COMPARISON WITH OTHER PUBLISHED WORK**

### **6.1 Introduction**

In this chapter, analysis and results of the models used in this work are compared with published work based on abductive networks [48]. Both approaches are applied to the same set of data. As mentioned previously, the used data source in this analysis consists of measured hourly load consumption in MW and temperature in Fahrenheit for the Puget power utility, Seattle, USA, over the period from 1 January 1985 to 31 December 1990. Years from 1985 to 1989 are used for training and model building to forecast next hour and next day load for the year 1990. First, an overview of reference [48] is presented showing the concept and history of the abductive networks. Then, for next hour and next day load forecasting, inputs parameters, used

approach and results are shown. After that, for each model, the obtained results from abductive networks model are compared with the obtained results from the models used in this work; all are applied to the same set of data.

## **6.2 Abductory Inductive Mechanism (AIM) Networks**

AIM is a supervised inductive machine-learning tool for synthesizing automatically abductive network models from a database of inputs and outputs to represent training set of solved examples. This tool can automatically synthesize sufficient models that embody the inherent structure of complex and highly nonlinear systems. The group method of data handling (GMDH) technique [49-50] is a formalized paradigm for iterated (multi-phase) polynomial regression that can produce a high-degree polynomial model in effective predictors. The process is naturally 'evolutionary', using initially simple regression relationships to derive more accurate representations in the next iteration. The algorithm selects input combinations and polynomial relationships that help minimizing the prediction error in each phase. AIM builds networks of different forms of polynomial functional elements, according to prediction performance. The element types, network size, connectivity, and coefficients for the optimum model are determined automatically by using well-proven optimization criteria, thus reducing the need for user intervention compared to neural networks. This simplifies model development and considerably decreases the learning/development effort and time. The models take the form of layered feed-forward abductive networks of functional elements (nodes) as shown in figure 6.1.

[49]

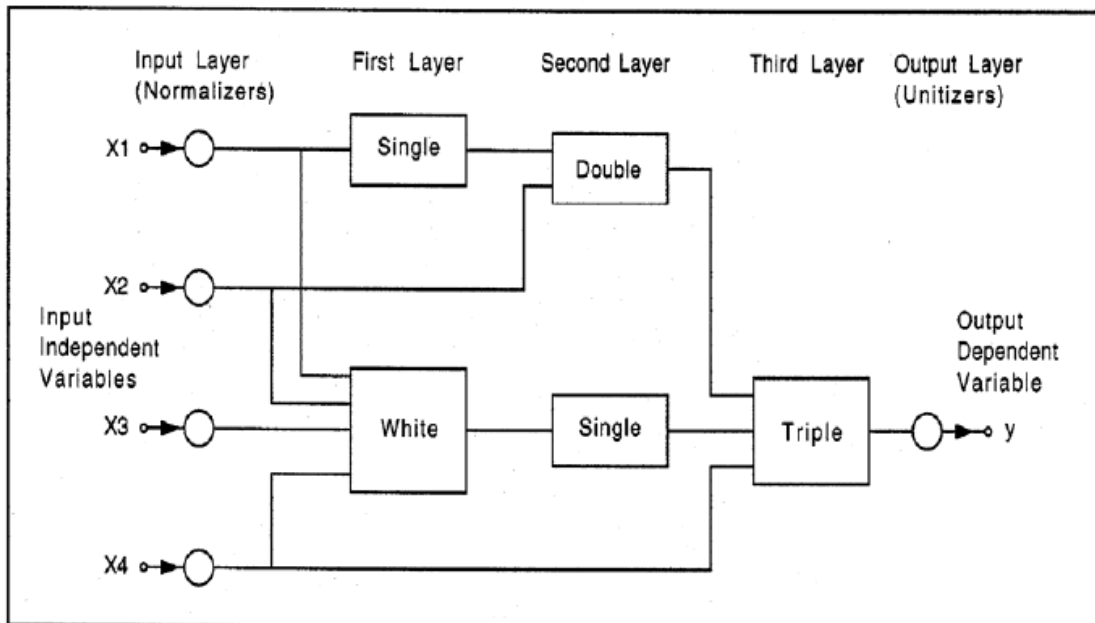


Figure 6.1: A typical AIM abductive network model showing various types of functional elements.

The elements in the first layer operate on different combinations of the independent input variables ( $X$ 's) and the element in the final layer produces the predicted output for the dependent variable  $y$ . In addition to the main layers of the network, an input layer of normalizers convert the input variables into an internal representation as  $Z$  scores with zero mean and unity variance.

The used version of AIM supports the following main functional elements:

- (i) A white element which consists of a constant plus the linear weighted sum of all outputs of the previous layer, i.e.:

$$\text{“White” Output} = W_0 + W_1X_1 + W_2X_2 + W_3X_3 + \dots + W_nX_n \quad (6.1)$$

Where  $X_1, X_2, \dots, X_n$  are the inputs to the element and  $W_0, W_1, \dots, W_n$  are the element weights.

(ii) Single, double, and triple elements which implement a third-degree polynomial expression with all possible cross-terms for one, two, and three inputs respectively; for example,

$$\text{“Double” Output} = W_0 + W_1X_1 + W_2X_2 + W_3X_1^2 + W_4X_2^2 + W_5X_1X_2 + W_6X_1^3 + W_7X_2^3 \quad (6.2)$$

The database of input-output solved examples is divided into a training set and an evaluation set. AIM uses the training set to synthesize the model network layer by layer until no further improvement in performance is possible or a preset limit on the number of layers is reached. Within each layer, each element is computed and its performance scored for all combinations of allowed inputs. The best network structure, element types and coefficients, and connectivity are all determined automatically by minimizing the predicted squared error (PSE) criterion [51], which eliminates the problem of determining when to stop training in neural networks. This criterion selects the most accurate model that does not overfit the training data to strike a balance between the accuracy of the model in representing the training data and its generality which allows it to fit yet unseen future data. The user may optionally control this trade-off between accuracy and generality using the complexity penalty multiplier (CPM) parameter. Larger values than the default value of 1 lead to simpler models that are less accurate but may generalize well with previously unseen data, while lower values produce more complex networks that may overfit the training data and degrade actual prediction performance. [49]



## 6.3 Next Hour Load Forecasting

### 6.3.1 Abductive Networks Model

In this model, 24 models are developed to forecast the load at the next hour ( $h$ ) within day ( $d$ ) where the inputs are all hourly load data on day ( $d-1$ ) ( $L_1, L_2, L_3, \dots, L_{24}$ ) and all available hourly load data on day ( $d$ ) up to, and including, the preceding hour ( $h-1$ ) ( $NL_1, NL_2, \dots, NL_{(h-1)}$ ) in addition to extreme temperatures and day type information. In next hour load forecasting model, the number of load inputs is not fixed. It varies between 24 inputs for hour 1 and 47 inputs for hour 24. Moreover, other inputs include the average temperature  $T_a$  on day ( $d-1$ ) and the forecasted average temperature  $ET_a$  for day ( $d$ ). Also, day type for the forecasting day ( $d$ ) was represented by a single binary input ( $WRK$ ) that is 1 for a working day and 0 otherwise. A record in the training dataset for the model for hour  $h$ , where  $h=2,3,\dots,24$  takes the form of table 6.1:

Table 6.1: Inputs parameters configuration for next hour load forecasting

Inputs					Output
24 hourly loads for day ( $d-1$ )	( $h-1$ ) available hourly loads on day ( $d$ )	Average temperature for day ( $d-1$ )	Forecasted average temperature for day ( $d$ )	Day type code for day ( $d$ )	Load for hour ( $h$ ) on day ( $d$ )
$L_1, L_2, L_3, \dots, L_{24}$	$NL_1, NL_2, \dots, NL_{(h-1)}$	$T_a$	$ET_a$	$wrk$	$L(d,h)$

Also, table 6.2 summarizes the model structure for all the 24 hourly models and lists the model inputs selected and the corresponding time lags in the load time series and shows a sketch of the model structure.

Table 6.2: Summary of the abductive network models for the 24 next-hour load forecasters

Day (d) Forecasting Hour	Model Input(s)			Load Time Lags Selected	Model Structure
	Day (d-1) Load at Hours:	Day (d) Load at Hours:	Other		
2		1		1	
3		2		1	
4		3		1	
8		7		1	
7		6,5		1,2	
1	24,20,3			1,5,22	
5	10	4	WRK	1,19	
6	22	5,1		1,5,8	
9		8,6,4		1,3,5	
10	18	9,8		1,2,16	
11	16	10,9		1,2,19	
12		11,9,8		1,3,4	
13		12,10,7		1,3,6	
14		13,10,8		1,4,6	
15		14,11,8		1,4,7	
17	18,11	16		1,13,20	
19		18,16,9		1,3,10	
20	20,18	19		1,24,26	
21	22,20	20		1,23,25	
22	23,20	21		1,23,26	
23	23,21	22		1,24,26	
18		17,15,9	Ta	1,3,9	
24	19,9	23,22	WRK	1,2,29,39	

### 6.3.2 ANN Model

For next hour load forecasting modeled in this work, the inputs parameters and values arrangement follow the same approach done for SEC and Marafiq data. Figure 6.2 shows the actual and forecasted load in addition to MAPE and absolute errors for

for the entire year 1990 of Seattle, USA on the basis of next hour load forecasting using NN.

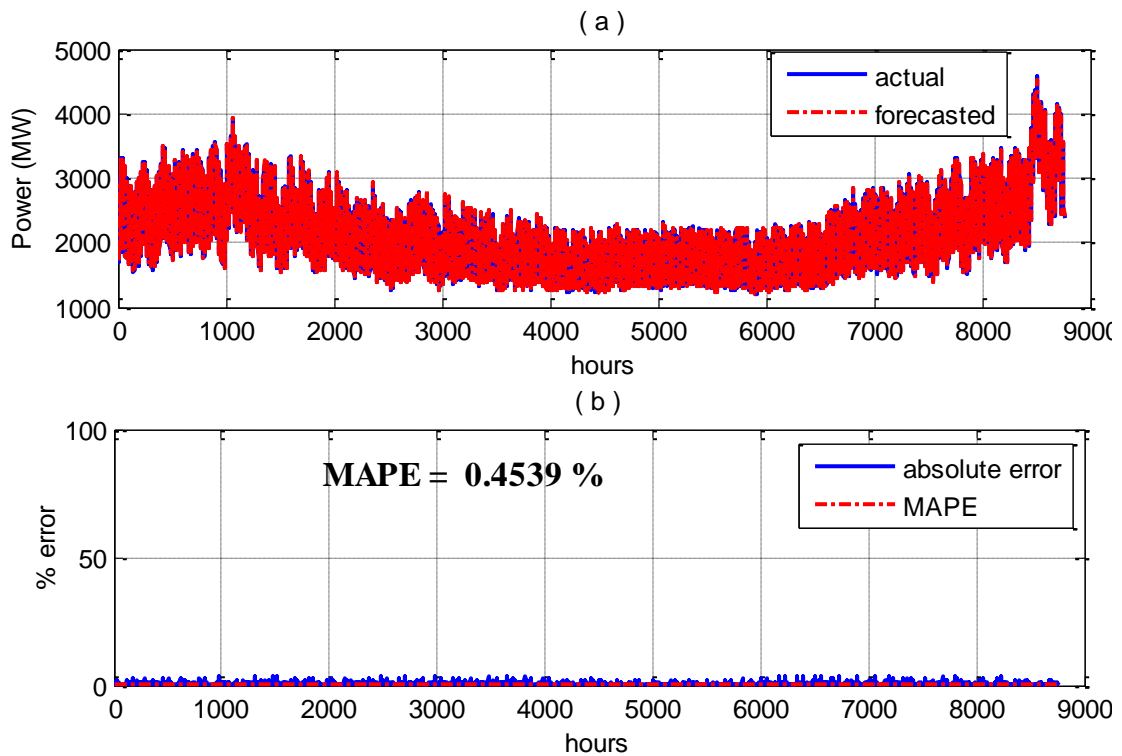


Figure 6.2: a) Actual and forecasted load for year 1990, Seattle, USA  
b) Absolute error and MAPE, next hour, NN model

It is clear that next hour load forecasting model using ANN has accurately forecasted next hour load for the year 1990. The performance of the model gives accurate results for implementation and indicates the validity of the proposed model.

### 6.3.3 Hybrid Analytical Model

For next hour load forecasting using the hybrid analytical model, the same approach followed for SEC and Marafiq data will be applied to USA data. The difference is in the nature of modes because of different characteristics of USA data. For example, some new modes like Thanksgiving day, Labor day, Christmas day are present here. Moreover, unlike KSA, weekend days in USA are Saturdays and

Sundays. Figure 6.3 shows the actual and forecasted load in addition to MAPE and absolute errors for for the entire year 1990 of Seattle, USA on the basis of next hour load forecasting using hybrid analytical model.

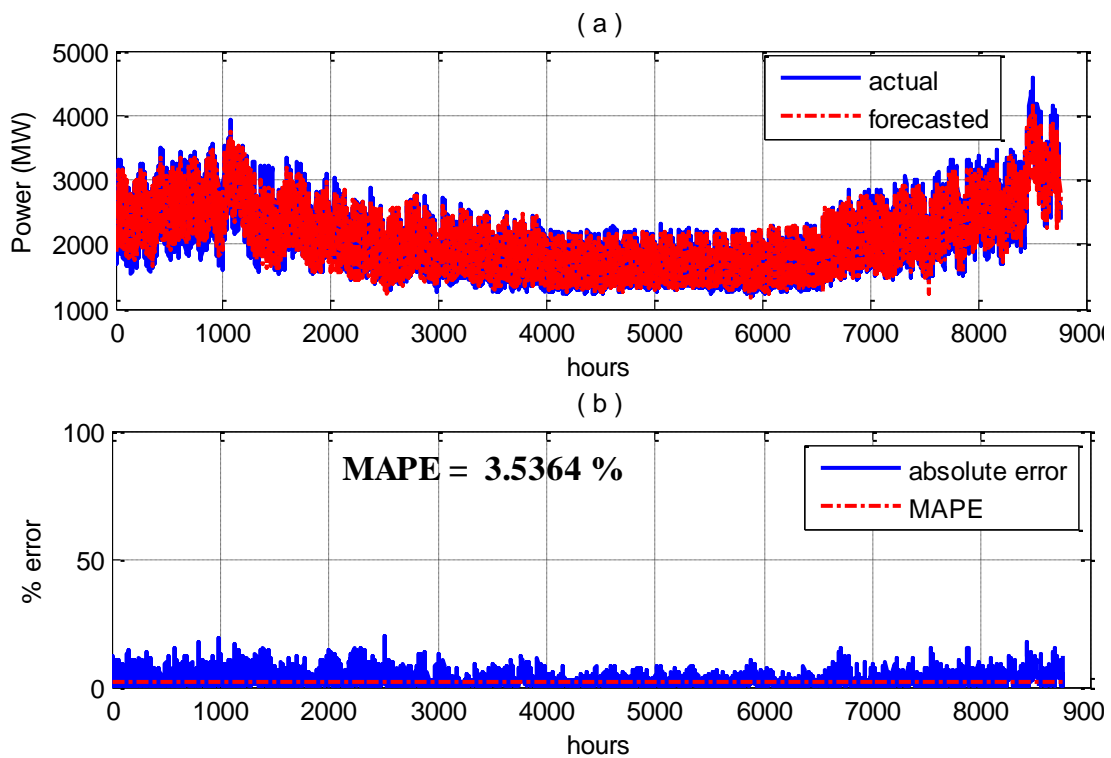


Figure 6.3: a) Actual and forecasted load for year 1990, Seattle, USA  
b) Absolute error and MAPE, next hour, Hybrid analytical model

So, the hybrid analytical model gives relatively satisfactory results for next hour load forecasting for the year 1990. The hybrid analytical model forecasts the holidays in better accuracy than normal days because these holidays are mainly affected by people activities and the impact of weather variables is limited. For example, in Christmas day, people activities are the same each year and this gives a clear indication of the forecasted Christmas day based on the records of previous year's Christmas days. Consequently, load behavior for the holidays does not change each year.

In comparing the results of all next hour models (abductive networks, ANN and hybrid analytical models), table 6.3 lists the MAPE values for all hours, giving the overall value for the evaluation year as 1.14 % reached by the abductive networks model and 0.4539 % reached by ANN model and 3.5364 % reached by the hybrid analytical model, which indicates the effectiveness of such models for STLF.

Table 6.3: Performance of next-hour load forecasting models over the evaluation year

Forecasting Hour, h	MAPE, %		
	Abductive Networks Model	ANN Model	Hybrid Analytical Model
1	1.14	0.3376	3.59
2	1.01	0.3762	4.1279
3	0.93	0.4142	4.3975
4	0.88	0.4609	4.2138
5	1.08	0.8437	3.9596
6	1.27	1.2241	3.8487
7	2.08	0.5297	3.8128
8	1.55	0.6398	3.4294
9	1.28	0.3797	2.6909
10	0.82	0.297	2.1754
11	0.94	0.2903	2.2206
12	0.7	0.3982	2.5677
13	0.8	0.323	3.0541
14	0.69	0.3461	3.5914
15	0.7	0.3835	3.9610
16	0.77	0.4024	4.2641
17	1.27	0.4207	4.7407
18	1.31	0.4066	4.9125
19	1.48	0.3769	4.3062
20	1.25	0.4022	3.3790
21	1.59	0.4228	2.9460
22	1.23	0.4653	2.7520
23	1.2	0.3675	2.8381
24	1.29	0.3855	3.3031
Average	1.14	0.4539	3.5364

Therefore, ANN next hour load forecasting model used in this work gives better results than the abductive networks and hybrid analytical models. The inputs used in the ANN model include all the previous hours (from h-1 up to h-24) loads to the forecasted hour. The model includes the most up to date load variation and the impact of the surrounding environment contribution.

## **6.4 Next Day Load Forecasting**

### **6.4.1 Abductive Networks Model**

In next day load forecasting, 24 models are developed which forecast the full hourly load curve for the following day (d) in one go at the end of the preceding day (d-1). A model is dedicated for forecasting the load,  $EL(d,h)$ , for each hour of the day. Unlike the case of next hour load forecasting where number of inputs is not fixed, all models here use the same set of inputs which includes: 24 hourly loads at day (d-1) ( $L_1, L_2, L_3, \dots, L_{24}$ ), the measured minimum ( $T_{min}$ ) and maximum ( $T_{max}$ ) air temperatures on day (d-1), the forecasted minimum ( $ET_{min}$ ) and maximum ( $ET_{max}$ ) air temperatures on day (d), and the day type for forecasting day (d). The day type was coded as four mutually exclusive binary inputs representing a working day (Monday to Friday) (WRK), a Saturday (SAT), a Sunday (SUN), and an official holiday (HOLI).  $T_{min}$  and  $T_{max}$  were taken as the minimum and maximum values of the 24 hourly temperatures provided for the day. A record in the training dataset for the model for hour h ( $h=1,2,\dots,24$ ) includes 32 input variables and takes the form of table 6.4. Moreover, table 6.5 summarizes the model structure for all the 24 models, listing the model inputs selected and the number of layers and elements. Models for the first two hours discard temperature and day type information, relying only on the load time

series. Forecasted temperature and day type inputs feature in all remaining models. Model complexity and nonlinearity increases as the forecasting hour progresses and the lead time increases.

Table 6.4: Inputs parameters configuration for next day load forecasting

Inputs				Output
24 hourly loads for day (d-1)	Extreme Temperatures for day (d-1)	Forecasted Extreme Temperatures for day (d)	Day type code for day (d)	Load for hour (h) on day (d)
L1, L2, L3.....L24	Tmin, Tmax	ETmin, Etmax	wrk,sun,sat,holi	L(d,h)

Full-day load curves were forecasted using all 24 models for four days of the evaluation year which represent a working day, a Saturday, a Sunday, and a holiday in the same season over the interval from 8 August to 3 September 1990. The results of these forecasted days using abductive networks are shown in figures 6.4a, 6.5a, 6.6a and 6.7a.

#### 6.4.2 ANN Model

For next day load forecasting modeled in this work, the inputs parameters and values arrangement follow the same approach done for SEC and Marafiq data. The model utilizes the previous historical load values up to a day before the forecasted hour, h in the day, d. The results of the mentioned forecasted days using ANN are shown in figures 6.4b, 6.5b, 6.6b and 6.7b.

#### 6.4.3 Hybrid Analytical Model

This model it is the same as the hybrid analytical next hour model. In next hour model, the mode equation is only evaluated at the forecasted hour; h. However, in next day model, the equation is evaluated at all hours of the day from 1 to 24. Forecasting next day average load is also same for both models. Therefore, hybrid analytical model

can be considered as next hour or next day load forecasting models. The results of the mentioned forecasted days using the hybrid analytical model are shown in figures 6.4c, 6.5c, 6.6c and 6.7c.

Table 6.5: Abductive network models for the 24 next-day hourly load forecasters

Day (d) Forecasting Hour	Model Inputs				Model Structure	
	Day (d-1) Load at Hours:	Temperature		Day (d) Day Type	Number of Layers	Total Number of Elements
		Day (d-1)	Day (d)			
1	3,20,24				1	1
2	17,21,24				1	1
3	1-13,15,17-24	Tmin	ETmin	WRK	1	1
4	1-24	Tmin	ETmin	WRK	1	1
5	1,3-5,7-24	Tmin, Tmax	ETmin	WRK, SAT, SUN	1	1
6	1-24	Tmin, Tmax	ETmin, ETmax	WRK, SAT, SUN	2	2
7	1-24	Tmin, Tmax	ETmin, ETmax	WRK, SAT, SUN	2	2
8	1-24	Tmin, Tmax	ETmin, ETmax	WRK, SAT, SUN	3	3
9	1-6,8-10,12-24	Tmin	ETmin, ETmax	WRK, SAT, SUN	2	2
10	1-24	Tmin, Tmax	ETmin, ETmax	WRK, SUN	3	3
11	7,15,21,24		ETmax	SUN	3	3
12	7,12,22,24		ETmin, ETmax	SUN	4	4
13	8,12,22	Tmax	ETmin, ETmax	WRK, SUN	4	4
14	2,8,13,22	Tmax	ETmin, ETmax	WRK, SUN	4	4
15	7,9,13,16,18,22	Tmax	ETmin, ETmax	WRK	4	5
16	1-15,17-24	Tmax	ETmin, ETmax	WRK, SUN	4	4
17	2,7,18,22	Tmax	ETmax	WRK	4	4
18	1-11,13-22,24	Tmin, Tmax	ETmax	WRK, SAT	2	2
19	1-11,13,14,16-24	Tmin, Tmax	ETmin, ETmax	WRK, SUN	2	2
20	4,8,20	Tmax	ETmax	WRK	3	3
21	1,7,16,21	Tmax	ETmax	WRK	3	3
22	1-13,15-24	Tmin, Tmax	ETmin, ETmax	WRK, SAT	2	2
23	1-3,5-7,9-12, 14,15-23	Tmin, Tmax	ETmin, ETmax	WRK	3	3
24	2,8,23	Tmin	ETmax	SUN	3	3



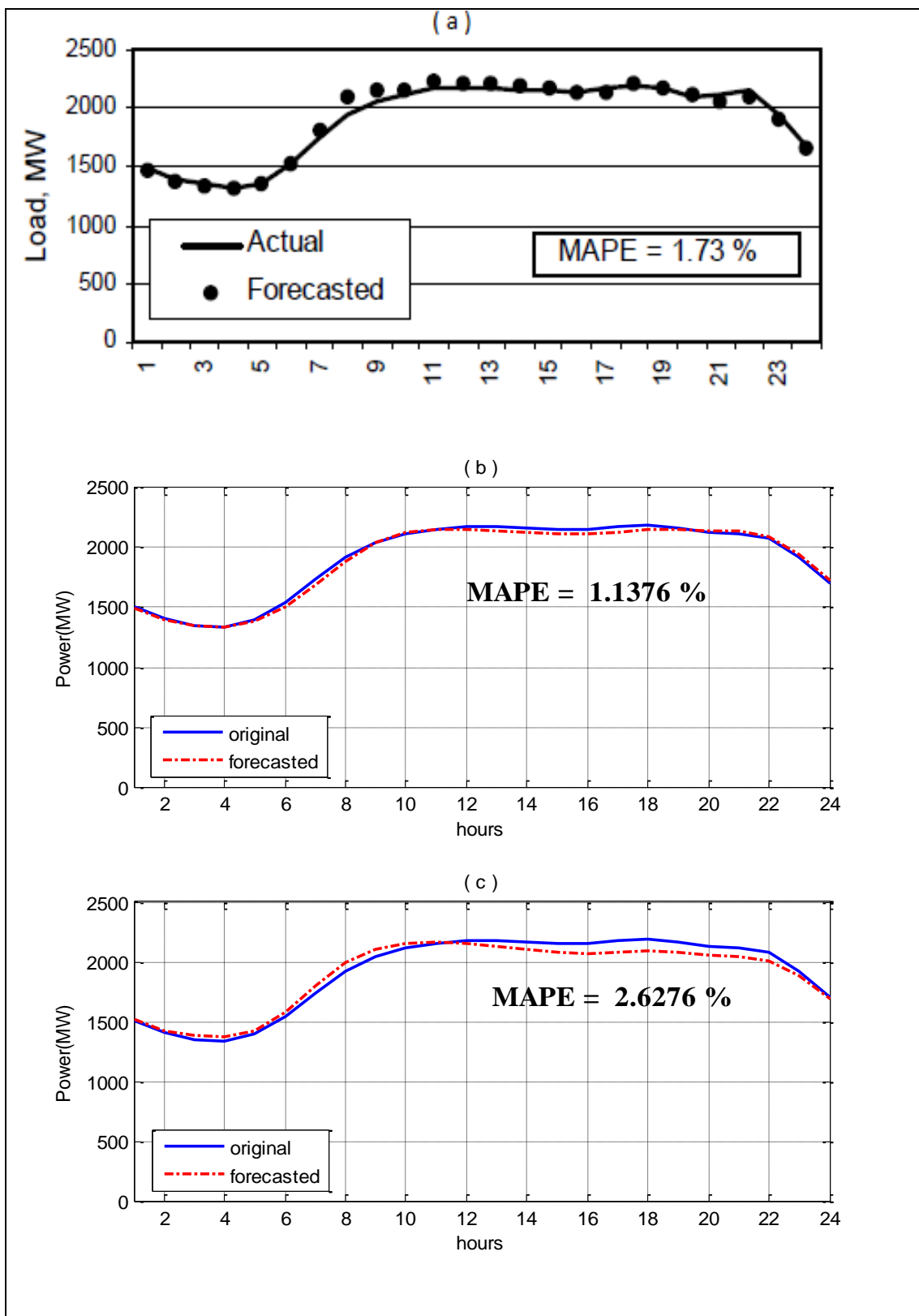


Figure 6.4: Actual and forecasted load profile for Wednesday 8 Aug, 1990 (working day) using:(a) abductive networks (b) ANN (c) hybrid analytical model

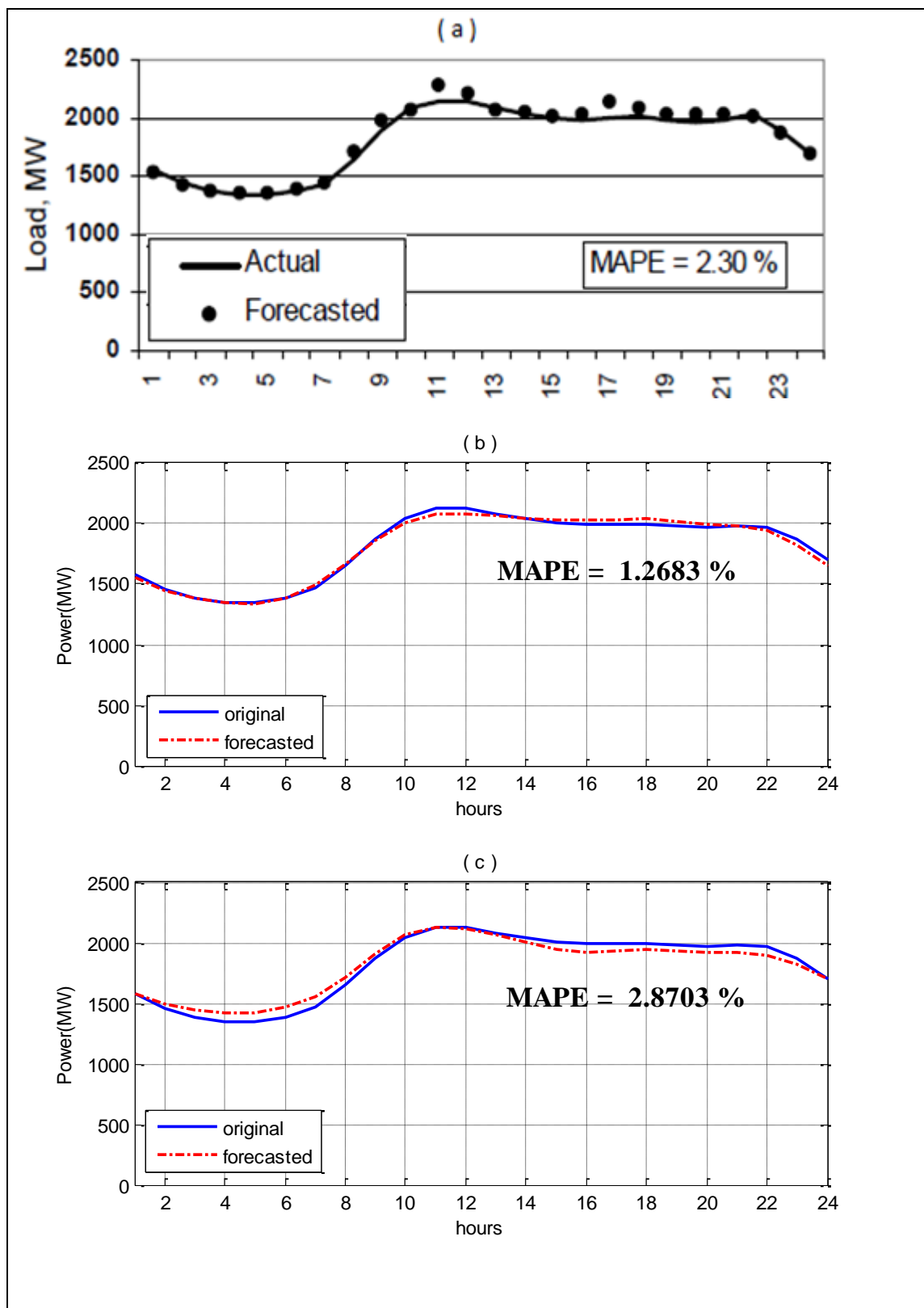


Figure 6.5: Actual and forecasted load profile for Saturday 11 Aug, 1990 (week end day) using: (a) abductive networks (b) ANN (c) hybrid analytical model

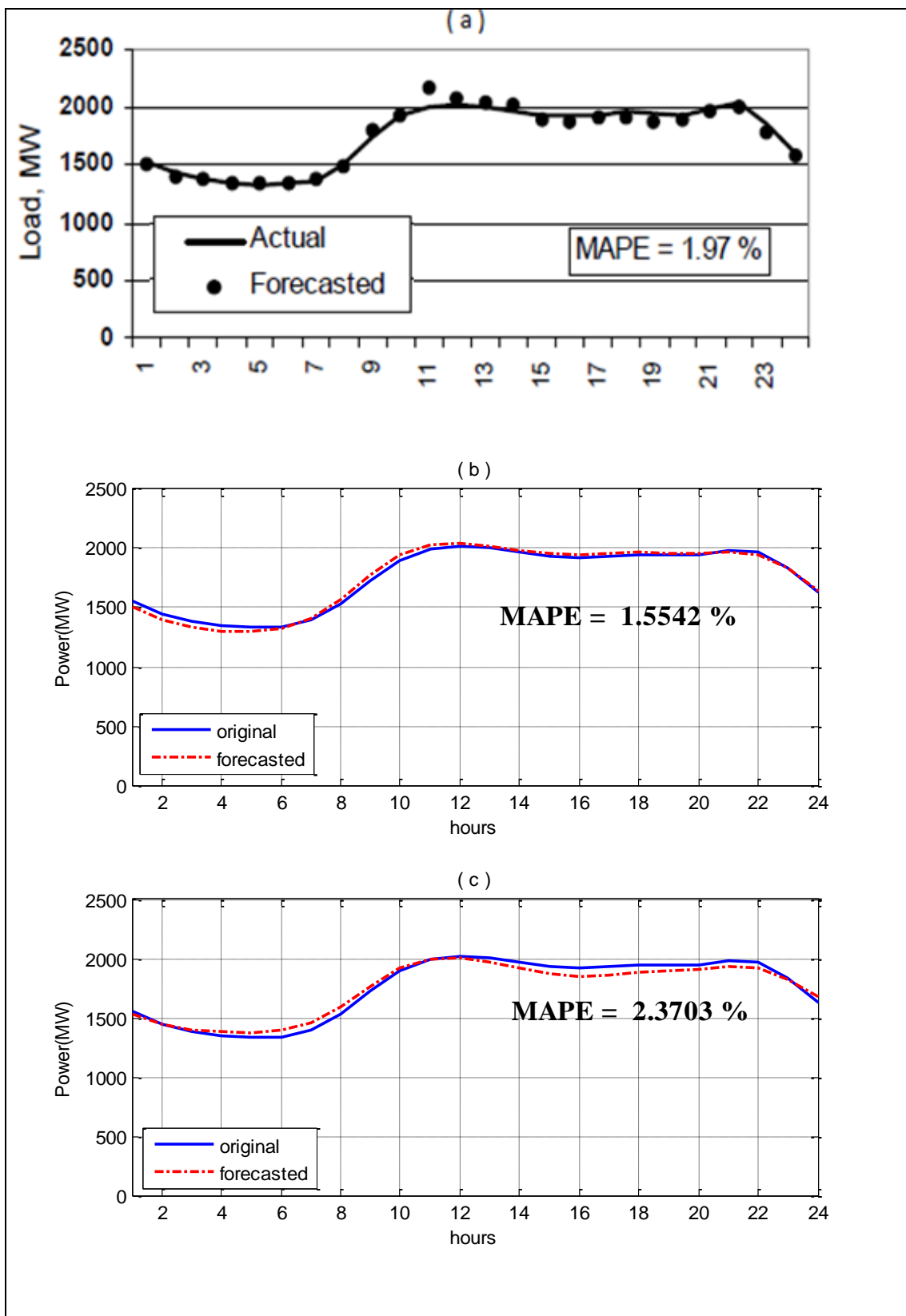


Figure 6.6: Actual and forecasted load profile for Sunday 12 Aug, 1990 (week end day) using: (a) abductive networks (b) ANN (c) hybrid analytical model

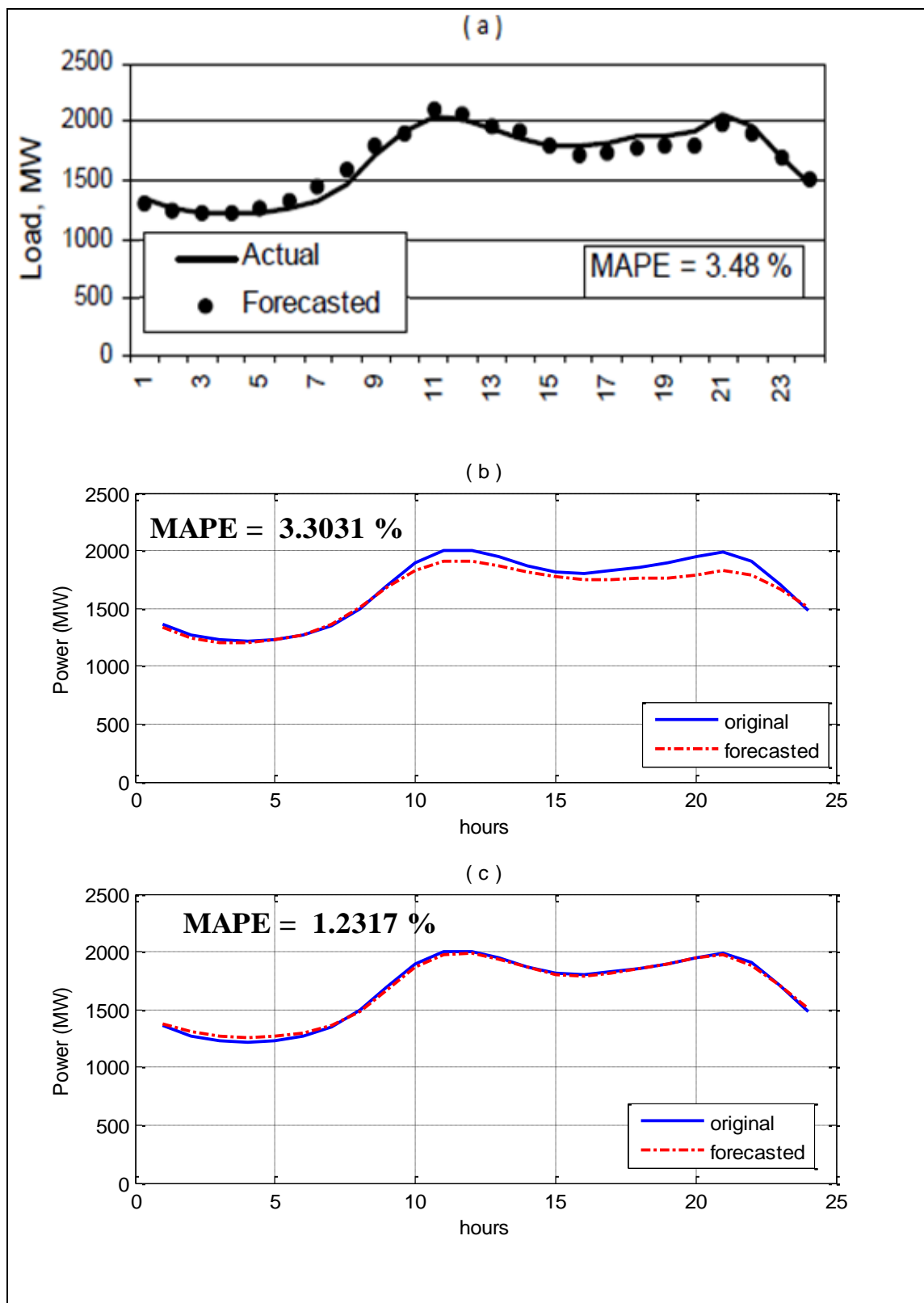


Figure 6.7: Actual and forecasted load profile for Monday 3 Sep, 1990 (Labor Day holiday) using: (a) abductive networks, (b) ANN (c) hybrid analytical model

### 6.4.4 Iterative Model

In addition, as done previously for SEC and Marafiq data, next day load forecasting can be modeled using repetitive use of next hour load models. Figure 6.8 shows the above mentioned sample days forecasted using this method.

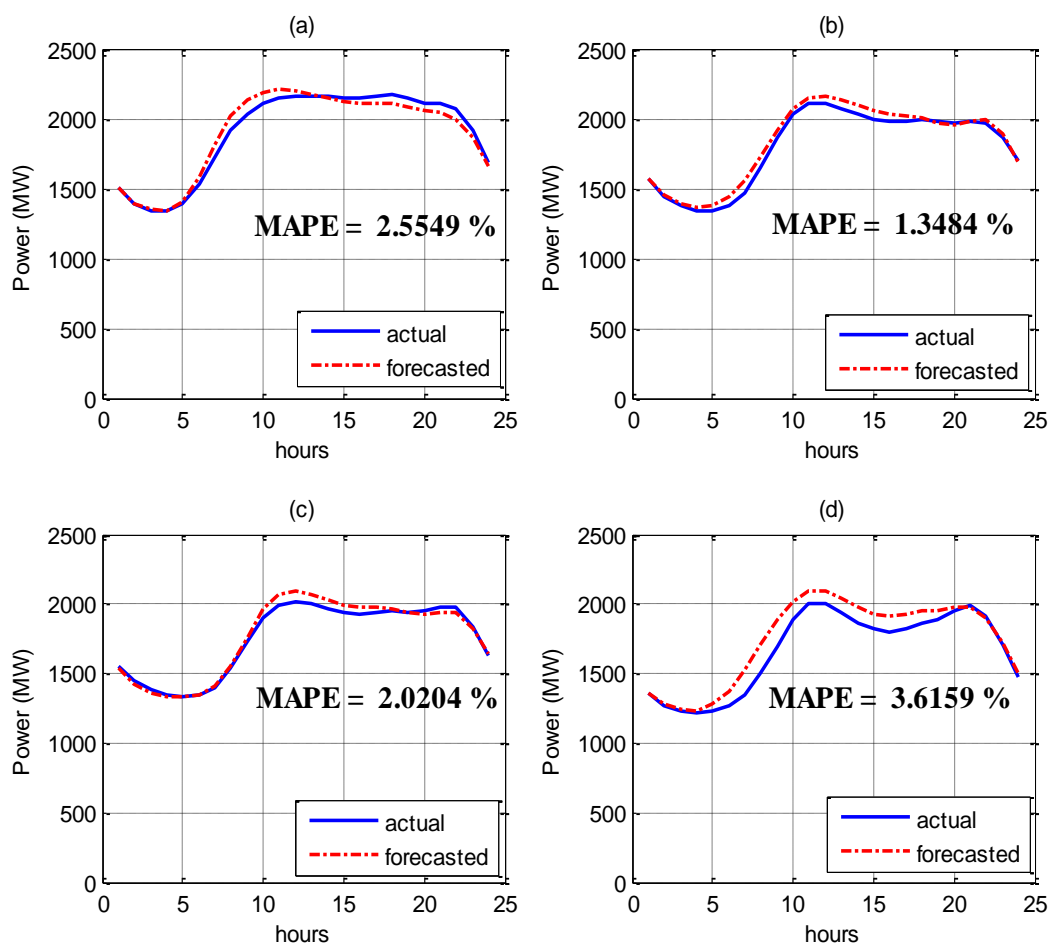


Figure 6.8: Actual and forecasted load profile using iterative model for:  
 (a) Wednesday 8 Aug, 1990 (b) Saturday 11 Aug, 1990  
 (c) Sunday 12 Aug, 1990 (d) Monday 3 Sep, 1990

Table 6.6 shows the MAPE comparison between the four models for each day for next day load forecasting.

Table 6.6: MAPE comparison between the four models for each day for next day load forecasting

	MAPE, %			
	8-Aug	11-Aug	12-Aug	3-Sep
ANN	1.1376	1.2683	1.5542	3.3031
Iterative	2.5549	1.3484	2.0204	3.6159
Hybrid	2.6276	2.8703	2.3703	1.2317
Abductive	1.73	2.3	1.97	3.48

For abductive networks model and ANN model, it is clear that the forecasting accuracy is the best for the working day and poorest for the holiday due to the fewer examples of holiday load patterns encountered during training. Moreover, the results obtained using iterative forecasting are very satisfactory. The best MAPE for the holiday day (Labor Day) is achieved by using the hybrid analytical model. This is because this day is considered as a mode and the model keeps its shape during all the model building years which are very similar in behavior as shown in figure 6.9. In holidays, load behavior is not affected by temperature considerably. The main affecting factor is people activities.

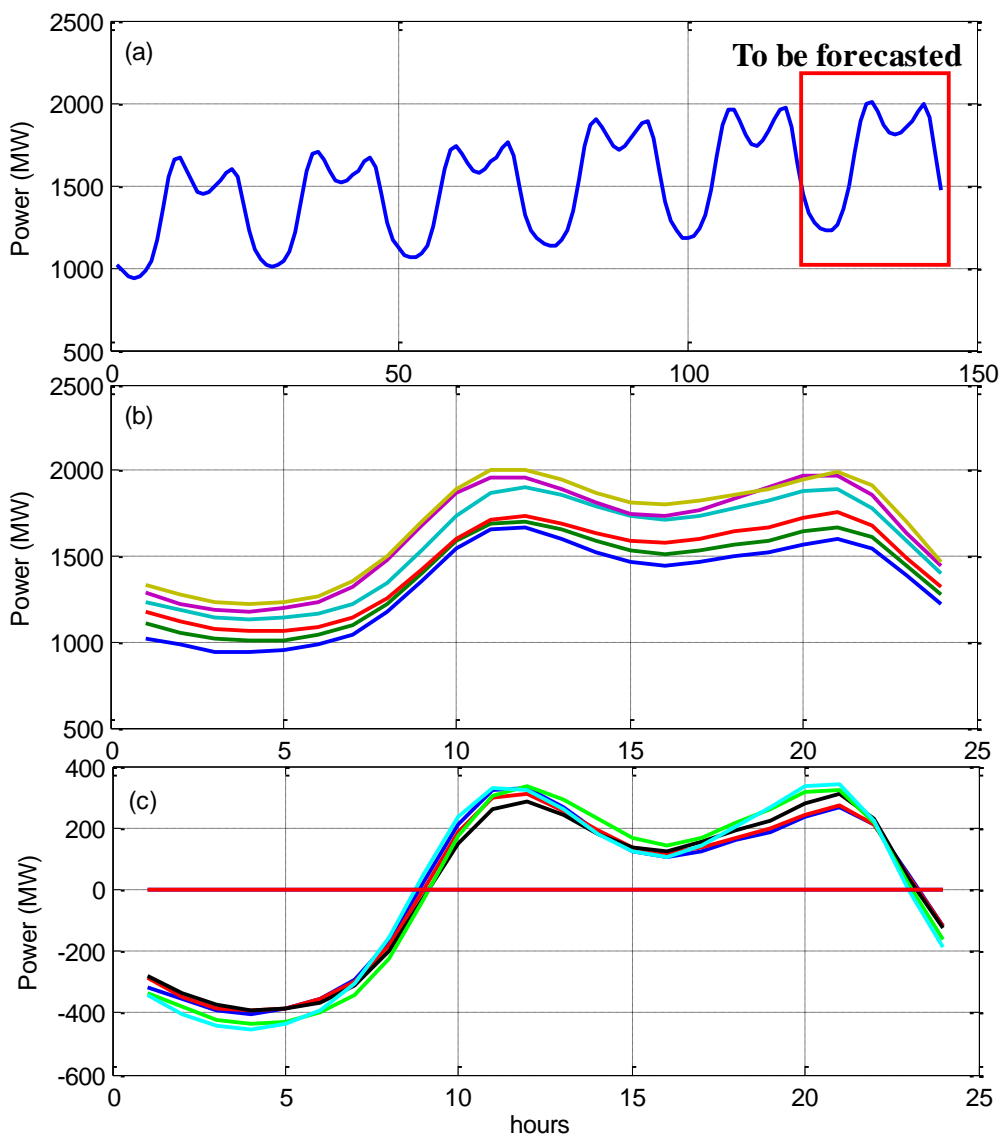


Figure 6.9: (a) Labor Day load profile for years 1985 – 1990  
 (b) Similarity of Labor Day load profile for years 1985 – 1989  
 (c) Ac components for Labor Day profile for years 1985 – 1989

So, after isolating the dc component (average value) for each day and placing the figures at the zero axes as shown in figure 6.9c, it is very obvious that they have very identical behavior and this interprets the low MAPE for this day using hybrid analytical model.

So, after finding this average day, Fourier transform analysis mentioned in chapter 4 is applied to its waveform to reach to the final model equation of this mode. Figure 6.10 shows the actual Labor Day for 1990 decomposed to its dc and ac components. Also, table 6.7 shows the amplitudes and phase angles for the actual Labor Day and the average mode day.

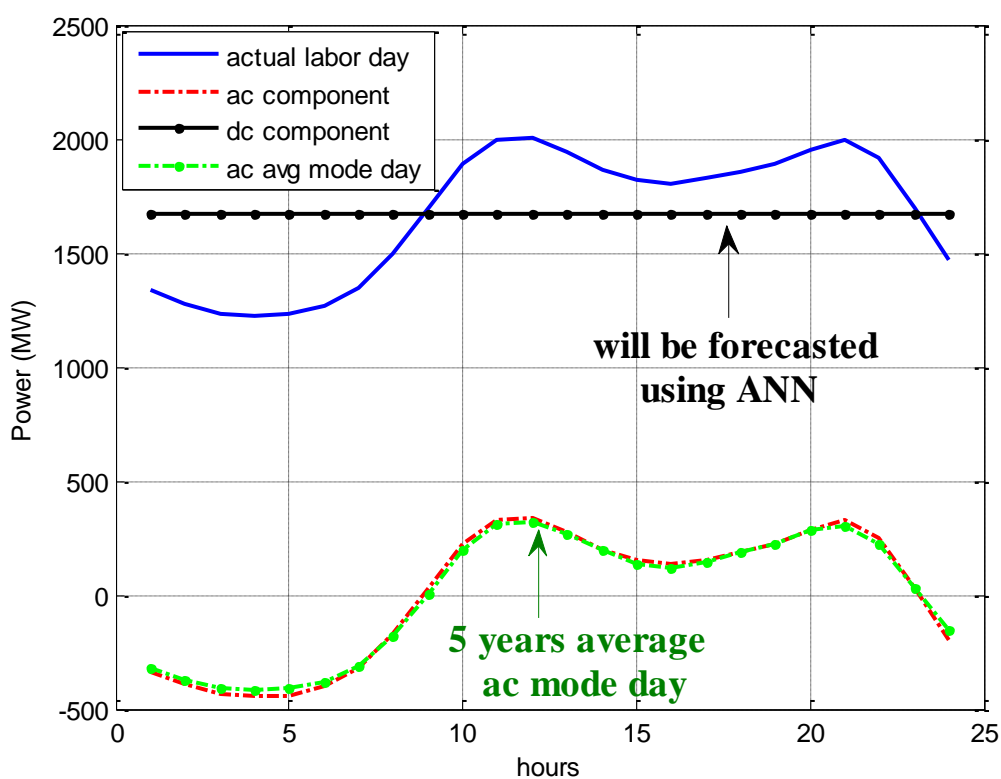


Figure 6.10: Actual Labor Day for 1990 decomposed to its dc and ac components



Table 6.7: Amplitudes and phase angles for the actual Labor Day and the five years average ac mode day

Amplitudes		Phase Angles	
Actual	Avg. ac	Actual	Avg. ac
1668.41	0	0	3.14159
175.402	175.4596	2.38011	2.37992
92.499	92.61892	1.53799	1.53808
33.8004	33.66315	-2.4279	-2.4308
19.2711	19.19291	3.11999	3.11
8.24533	8.01509	-1.7241	-1.7113
5.34924	5.172116	-1.3687	-1.3217

So, the equation for the 5 years average mode day is as follows:

$$\begin{aligned}
 P_{L\text{-avg-ac}} = & 175.46 \cdot \cos(w(t-1)+2.38) + 92.62 \cdot \cos(2w(t-1)+1.54) \\
 & + 33.66 \cdot \cos(3w(t-1)-2.43) + 19.19 \cdot \cos(4w(t-1)+3.11) \\
 & + 8.02 \cdot \cos(5w(t-1)-1.71) + 5.17 \cdot \cos(6w(t-1)-1.32)
 \end{aligned} \tag{6.3}$$

Where  $w = \frac{2\pi}{24}$ ,

t is the hour number from 1 to 24

Table 6.7 shows the high similarity between the actual Labor Day and the average ac mode day for the Labor Day. Since the mean value of the average mode day is zero, it is clear that its dc component is zero with phase angle  $\pi$ . Also, the dc component for the actual Labor Day is at zero frequency. The other harmonics amplitudes and phase angles are very identical for both days and these harmonics are the main responsible parameters for formatting the load curve shape.

## 6.5 Summary and Conclusions of the Chapter:

- The aim of this chapter is to compare the results obtained from all models used in this thesis with a published work using different methods applied to the same data set.
- For next hour load forecasting, NN model used in this work achieves MAPE of 0.4539 % overall the entire 1990 year where it is 1.14 % when forecasting using abductive networks. So NN model outperforms the abductive networks model by 0.6861 %.
- In next day load forecasting for the abductive networks and hybrid analytical models, the forecaster is limited to be at hour 24 of the day d-1 to forecast the day d. However, the advantage of the NN model is that it does not have such limitation. It is general for any hour in any day, and hence, it can be also considered as next 24 hours load forecasting rather than only next day load forecasting.
- The advantage of the hybrid analytical model is forecasting the modes that have few days with high accuracy. This is always present in special days like Labor Day, Thanksgiving days...etc. where each mode contains only one day each year avoiding grouping many days that affect the accuracy of modeling the average ac mode day.
- The obtained results for next day models conclude that when forecasting normal days, NN and abductive networks models achieve good results. However, to forecast special days or holidays, it is preferable to use hybrid analytical model.

## **CHAPTER 7**

### **CONCLUSIONS AND RECOMMENDATIONS**

This work studies the applicability of different ANN and analytical models on STLF. Residential STLF models are presented and applied to different types of loads exposed to distinct people activities and weather conditions. The analysis is carried out on residential areas for three regions in two countries which are Al-Khubar and Yanbu industrial city in KSA, in addition to Seattle, USA to show the validity of the proposed models applied on residential load. Various and diverse load characteristics are presented including high temperature, low temperature, high humidity, heating load, cooling load, different special days and different societies.

For each region, two models are proposed which are next hour and next day load forecasting. For next hour load forecasting, the model is proposed using ANN utilizing the historical load data up to the previous hour to the forecasted one. The obtained results show very accurate results for all areas. The MAPE for the evaluation

year gives 0.8131 % for SEC, 0.4869 % for Marafiq and 0.4539 % for USA over the entire evaluation year for each region which show the validity of all next hour load forecasting models.

In next day load forecasting, the analysis is conducted using two different techniques which are ANN and hybrid analytical model. In hybrid analytical model, days that have similar characteristics are classified to one group called mode. Then, representative average day for the mode is found and to construct the relevant model, Fourier Transform analysis is used. Then, ANN is used to forecast next day average power and finally the two components are combined to reach to the final next day forecasting using hybrid analytical model.

In ANN model, same approach followed in next hour model is applied here but with different inputs parameters utilizing historical load parameters up to the load at same forecasted hour at previous day. The two next day forecasting models yield reasonable results where MAPE values for the evaluation year are 3.4496 % and 4.2208 % for SEC, 3.2517 % and 4.3647 % for Marafiq, and % 2.6551 and 3.5364 % for USA, using ANN and hybrid analytical models, respectively.

To show the effectiveness of the proposed models, techniques used in this work were compared with other published work with different method. For next hour ANN load forecast, the proposed model gives better results than abductive networks model. The obtained results show that MAPE for ANN model for the evaluation year is 0.4539 % and for the abductive networks model is 1.14 %. In next day models, ANN and abductive networks models yield similar and satisfactory MAPE results for normal days when compared to the results obtained from the hybrid analytical model. However, using hybrid analytical model, it gives better results when forecasting

special days and holidays. MAPE values for the evaluation year for ANN, abductive networks and hybrid analytical models are 2.6551 %, 2.67 % and 3.5364 %, respectively.

As an extension of this work, further development models may include more weather parameters data such as wind speed and direction, rainfall and sky condition which have impact on the load. Also, this work is only to forecast next hour and next day loads. So, next week load forecasting could be a continuation for this work. Moreover, load type could be extended to include aggregated load, commercial and industrial loads. Hybrid analytical model could be used also for medium and long term forecasting but here the average daily load forecasting has to be extended to be not only next day average load forecasting but to include forecasting also to medium or long periods provided that accurate modes sorting should be achieved.

## APPENDIX A: List of Some Different Modes for All Data

SEC & Marafiq, KSA		Seattle, USA	
Mode	Code	Mode	Code
Cold normal days	1.1	New Year's Day	6
Cold Thursdays	1.6	Cold normal days	1.3
Cold Fridays	1.7	Cold Saturdays	1.1
Mid-year vacation	2	Cold Sundays	1.2
Hot normal days	3.1	Spring normal days	2.3
Hot Thursdays	3.6	Spring Saturdays	2.1
Hot Fridays	3.7	Spring Sundays	2.2
Eid Hajj day	11	Summer normal days	3.3
After Eid Hajj day	12	Summer Saturdays	3.1
Summer vacation normal days	5.1	Summer Sundays	3.2
Summer vacation Thursdays	5.6	Independence Day	11
Summer vacation Fridays	5.7	Labor Day	12
Ramadan days	6	Thanksgiving Day	14
Eid Feter day	8	Black Friday	15
After Eid Feter day	9	Christmas Day	17

## APPENDIX B: Sample Modes Days for SEC Data

SEC DATA									
d	m	y	h	T(C)	H(%)	P(MW)	dn	dy	mode
10	1	2002	1	17	46	11	6	10	1.6
10	1	2002	2	12	11	10	6	10	1.6
10	1	2002	3	12	11	9	6	10	1.6
10	1	2002	4	12	6	8	6	10	1.6
10	1	2002	5	12	2	8	6	10	1.6
10	1	2002	6	12	6	9	6	10	1.6
10	1	2002	7	13	10	9	6	10	1.6
10	1	2002	8	13	10	11	6	10	1.6
10	1	2002	9	13	19	13	6	10	1.6
10	1	2002	10	14	19	14	6	10	1.6
10	1	2002	11	18	26	15	6	10	1.6
10	1	2002	12	18	31	13	6	10	1.6
10	1	2002	13	19	36	13	6	10	1.6
10	1	2002	14	19	41	13	6	10	1.6
10	1	2002	15	19	44	12	6	10	1.6
10	1	2002	16	19	41	14	6	10	1.6
10	1	2002	17	19	37	16	6	10	1.6
10	1	2002	18	19	35	19	6	10	1.6
10	1	2002	19	19	35	17	6	10	1.6
10	1	2002	20	19	32	17	6	10	1.6
10	1	2002	21	19	32	16	6	10	1.6
10	1	2002	22	18	34	15	6	10	1.6
10	1	2002	23	18	35	14	6	10	1.6
10	1	2002	24	19	36	12	6	10	1.6
11	1	2002	1	19	35	11	7	11	1.7
11	1	2002	2	19	35	10	7	11	1.7
11	1	2002	3	19	36	9	7	11	1.7
11	1	2002	4	19	22	9	7	11	1.7
11	1	2002	5	19	12	8	7	11	1.7
11	1	2002	6	20	3	9	7	11	1.7
11	1	2002	7	20	10	8	7	11	1.7
11	1	2002	8	20	21	9	7	11	1.7
11	1	2002	9	22	22	10	7	11	1.7
11	1	2002	10	22	28	12	7	11	1.7
11	1	2002	11	23	32	13	7	11	1.7
11	1	2002	12	24	41	13	7	11	1.7

Cold Thursday , Schools Period

Cold Friday , Schools Period

11	1	2002	13	23	44	13	7	11	1.7
11	1	2002	14	22	46	13	7	11	1.7
11	1	2002	15	22	44	12	7	11	1.7
11	1	2002	16	22	46	13	7	11	1.7
11	1	2002	17	22	45	15	7	11	1.7
11	1	2002	18	20	32	16	7	11	1.7
11	1	2002	19	20	19	16	7	11	1.7
11	1	2002	20	20	31	16	7	11	1.7
11	1	2002	21	20	32	16	7	11	1.7
11	1	2002	22	13	34	15	7	11	1.7
11	1	2002	23	12	35	13	7	11	1.7
11	1	2002	24	12	36	13	7	11	1.7
12	1	2002	1	12	35	10	1	12	1.1
12	1	2002	2	12	22	9	1	12	1.1
12	1	2002	3	14	24	9	1	12	1.1
12	1	2002	4	14	25	8	1	12	1.1
12	1	2002	5	14	31	9	1	12	1.1
12	1	2002	6	14	37	11	1	12	1.1
12	1	2002	7	13	29	11	1	12	1.1
12	1	2002	8	11	42	12	1	12	1.1
12	1	2002	9	13	41	13	1	12	1.1
12	1	2002	10	13	42	13	1	12	1.1
12	1	2002	11	13	42	13	1	12	1.1
12	1	2002	12	14	43	12	1	12	1.1
12	1	2002	13	14	42	13	1	12	1.1
12	1	2002	14	14	44	13	1	12	1.1
12	1	2002	15	14	41	12	1	12	1.1
12	1	2002	16	14	43	14	1	12	1.1
12	1	2002	17	14	49	15	1	12	1.1
12	1	2002	18	12	50	19	1	12	1.1
12	1	2002	19	11	49	17	1	12	1.1
12	1	2002	20	11	49	18	1	12	1.1
12	1	2002	21	11	48	17	1	12	1.1
12	1	2002	22	11	46	16	1	12	1.1
12	1	2002	23	11	49	14	1	12	1.1
12	1	2002	24	10	51	12	1	12	1.1

Cold Week Day , Schools Period



### APPENDIX C: Sample Modes Days for Marafiq Data

Marafiq Data									
d	m	y	h	T(C)	H(%)	P(MW)	dn	dy	mode
14	8	2010	1	39.1087	18.0708	113.128	1	226	6.1
14	8	2010	2	37.2161	33.3944	112.402	1	226	6.1
14	8	2010	3	35.9341	49.2064	112.378	1	226	6.1
14	8	2010	4	34.3468	62.9426	113.101	1	226	6.1
14	8	2010	5	33.7363	95.9096	111.558	1	226	6.1
14	8	2010	6	32.6374	99.5116	107.142	1	226	6.1
14	8	2010	7	33.7363	99.5116	101.326	1	226	6.1
14	8	2010	8	35.5067	73.5653	103.059	1	226	6.1
14	8	2010	9	33.9194	99.3895	106.855	1	226	6.1
14	8	2010	10	34.4689	99.5116	109.449	1	226	6.1
14	8	2010	11	35.9341	99.5116	114.283	1	226	6.1
14	8	2010	12	36.4835	99.5116	118.726	1	226	6.1
14	8	2010	13	36.4835	99.4505	121.412	1	226	6.1
14	8	2010	14	37.4603	99.3895	125.105	1	226	6.1
14	8	2010	15	35.9951	99.5116	127.193	1	226	6.1
14	8	2010	16	36.6667	99.5116	129.051	1	226	6.1
14	8	2010	17	35.9341	99.5116	128.962	1	226	6.1
14	8	2010	18	34.2857	99.5116	128.25	1	226	6.1
14	8	2010	19	33.7973	99.5116	120.716	1	226	6.1
14	8	2010	20	33.3089	99.5116	125.416	1	226	6.1
14	8	2010	21	33.1868	99.5116	124.471	1	226	6.1
14	8	2010	22	32.6374	99.5116	122.257	1	226	6.1
14	8	2010	23	32.6984	99.5116	121.63	1	226	6.1
14	8	2010	24	32.6374	99.5116	119.801	1	226	6.1
10	9	2010	1	35.3846	15.4457	65.3472	7	253	8
10	9	2010	2	35.3846	15.3236	63.5446	7	253	8
10	9	2010	3	34.5299	19.7192	62.1494	7	253	8
10	9	2010	4	32.0879	47.1306	60.5916	7	253	8
10	9	2010	5	35.812	16.5446	60.6401	7	253	8
10	9	2010	6	34.591	22.2222	58.5271	7	253	8
10	9	2010	7	34.0415	20.8181	52.09	7	253	8
10	9	2010	8	32.7595	64.1026	57.0911	7	253	8
10	9	2010	9	36.7888	22.0391	60.3435	7	253	8
10	9	2010	10	36.1783	26.6178	64.5703	7	253	8
10	9	2010	11	34.4078	48.9011	66.8179	7	253	8
10	9	2010	12	35.5067	58.8523	69.7519	7	253	8

Ramadan Week Day

Eid Feter Day

10	9	2010	13	34.8352	80.525	70.8409	7	253	8
10	9	2010	14	35.3236	85.1648	71.2737	7	253	8
10	9	2010	15	35.1404	75.9463	70.5561	7	253	8
10	9	2010	16	34.0415	99.5116	69.8504	7	253	8
10	9	2010	17	33.6142	99.5116	67.8803	7	253	8
10	9	2010	18	32.3932	99.5116	66.114	7	253	8
10	9	2010	19	32.3932	99.5116	71.0527	7	253	8
10	9	2010	20	32.3321	99.5116	71.8739	7	253	8
10	9	2010	21	33.0647	99.5116	70.289	7	253	8
10	9	2010	22	35.3236	37.6068	68.4604	7	253	8
10	9	2010	23	34.7131	31.1966	64.7265	7	253	8
10	9	2010	24	32.3321	56.4103	64.7134	7	253	8
11	9	2010	1	31.4164	99.5116	64.4665	1	254	9.1
11	9	2010	2	31.8437	65.0794	63.6117	1	254	9.1
11	9	2010	3	30.7448	99.5116	60.9827	1	254	9.1
11	9	2010	4	31.8437	46.7643	58.9079	1	254	9.1
11	9	2010	5	30.3175	54.9451	59.5111	1	254	9.1
11	9	2010	6	29.2186	99.5116	59.5694	1	254	9.1
11	9	2010	7	29.2186	99.5116	55.2265	1	254	9.1
11	9	2010	8	31.9658	99.5116	57.0333	1	254	9.1
11	9	2010	9	31.4164	58.486	61.6569	1	254	9.1
11	9	2010	10	32.0879	70.696	64.7363	1	254	9.1
11	9	2010	11	33.3089	66.3004	67.2959	1	254	9.1
11	9	2010	12	34.2857	85.348	70.4059	1	254	9.1
11	9	2010	13	34.0415	74.9695	72.8075	1	254	9.1
11	9	2010	14	34.8352	65.0183	71.9531	1	254	9.1
11	9	2010	15	35.1404	64.8352	70.9466	1	254	9.1
11	9	2010	16	33.431	79.8535	70.5435	1	254	9.1
11	9	2010	17	32.9426	99.5116	70.2485	1	254	9.1
11	9	2010	18	32.0879	99.5116	68.0937	1	254	9.1
11	9	2010	19	30.989	99.5116	72.8252	1	254	9.1
11	9	2010	20	30.7448	99.5116	73.0765	1	254	9.1
11	9	2010	21	30.989	99.5116	72.4852	1	254	9.1
11	9	2010	22	31.2943	99.5116	69.921	1	254	9.1
11	9	2010	23	30.8669	99.5116	67.908	1	254	9.1
11	9	2010	24	32.3932	67.8266	65.3297	1	254	9.1

After Eid Feter Day

## APPENDIX D: Sample Modes Days for USA Data

USA DATA								
d	m	y	h	T(C)	P(MW)	dn	dy	mode
2	1	1989	1	4.44444	1794	3	2	1.3
2	1	1989	2	4.44444	1686	3	2	1.3
2	1	1989	3	5	1661	3	2	1.3
2	1	1989	4	5	1658	3	2	1.3
2	1	1989	5	5	1698	3	2	1.3
2	1	1989	6	5	1803	3	2	1.3
2	1	1989	7	5	1974	3	2	1.3
2	1	1989	8	5.55556	2184	3	2	1.3
2	1	1989	9	5.55556	2472	3	2	1.3
2	1	1989	10	5.55556	2733	3	2	1.3
2	1	1989	11	5.55556	2892	3	2	1.3
2	1	1989	12	5.55556	2885	3	2	1.3
2	1	1989	13	6.11111	2799	3	2	1.3
2	1	1989	14	6.66667	2687	3	2	1.3
2	1	1989	15	7.22222	2579	3	2	1.3
2	1	1989	16	7.22222	2578	3	2	1.3
2	1	1989	17	7.22222	2698	3	2	1.3
2	1	1989	18	7.22222	2851	3	2	1.3
2	1	1989	19	7.22222	2811	3	2	1.3
2	1	1989	20	7.22222	2748	3	2	1.3
2	1	1989	21	7.22222	2613	3	2	1.3
2	1	1989	22	7.77778	2408	3	2	1.3
2	1	1989	23	7.77778	2128	3	2	1.3
2	1	1989	24	8.33333	1839	3	2	1.3
11	6	1989	1	15	1313	2	162	3.2
11	6	1989	2	15	1223	2	162	3.2
11	6	1989	3	12.7778	1172	2	162	3.2
11	6	1989	4	12.7778	1166	2	162	3.2
11	6	1989	5	12.7778	1162	2	162	3.2
11	6	1989	6	10.5556	1168	2	162	3.2
11	6	1989	7	13.8889	1232	2	162	3.2
11	6	1989	8	16.1111	1401	2	162	3.2
11	6	1989	9	17.2222	1624	2	162	3.2
11	6	1989	10	18.3333	1800	2	162	3.2
11	6	1989	11	20.5556	1863	2	162	3.2
11	6	1989	12	21.6667	1860	2	162	3.2

Winter Week Day

Summer Sunday

11	6	1989	13	22.2222	1809	2	162	3.2
11	6	1989	14	25	1764	2	162	3.2
11	6	1989	15	26.6667	1697	2	162	3.2
11	6	1989	16	27.7778	1674	2	162	3.2
11	6	1989	17	28.3333	1711	2	162	3.2
11	6	1989	18	27.7778	1761	2	162	3.2
11	6	1989	19	27.2222	1767	2	162	3.2
11	6	1989	20	24.4444	1779	2	162	3.2
11	6	1989	21	22.2222	1808	2	162	3.2
11	6	1989	22	19.4444	1891	2	162	3.2
11	6	1989	23	18.8889	1778	2	162	3.2
11	6	1989	24	15.5556	1509	2	162	3.2
4	9	1989	1	59	1288	3	247	12
4	9	1989	2	57	1208	3	247	12
4	9	1989	3	58	1180	3	247	12
4	9	1989	4	54	1173	3	247	12
4	9	1989	5	52	1178	3	247	12
4	9	1989	6	54	1236	3	247	12
4	9	1989	7	54	1290	3	247	12
4	9	1989	8	55	1455	3	247	12
4	9	1989	9	60	1687	3	247	12
4	9	1989	10	64	1893	3	247	12
4	9	1989	11	66	2000	3	247	12
4	9	1989	12	70	1968	3	247	12
4	9	1989	13	70	1890	3	247	12
4	9	1989	14	73	1808	3	247	12
4	9	1989	15	74	1734	3	247	12
4	9	1989	16	74	1717	3	247	12
4	9	1989	17	73	1764	3	247	12
4	9	1989	18	70	1839	3	247	12
4	9	1989	19	68	1902	3	247	12
4	9	1989	20	66	1953	3	247	12
4	9	1989	21	63	2043	3	247	12
4	9	1989	22	62	1886	3	247	12
4	9	1989	23	60	1620	3	247	12
4	9	1989	24	59	1395	3	247	12

Labor Day



```

pt1=data(1:end-1,start_test:start_test+ih); % input for testing
ta1 = data(end,start_test:start_test+ih) ; % output to be compared
with the predicted one

%model simulation
pt1n = mapminmax('apply',pt1,ps);
pf1n = sim(net,pt1n);
pf1 = mapminmax('reverse',pf1n,ts);
e1=100*(ta1-pf1)./ta1;

mapel=mean(abs(e1));

subplot(211)
plot(ta1,'LineWidth',1.5);hold on
plot(pf1,'-.r','LineWidth',1.5);grid
legend('actualal','forecasted')
title('( a )');xlabel('hours');ylabel('Power (MW)')

subplot(212)
plot(abs(e1),'b','LineWidth',1.5);hold on
plot(repmat(mapel,length(e1),1),'-.r','LineWidth',1.5);grid
legend('absolute error','MAPE')
title('( b )');xlabel('hours');ylabel('% error')

```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% FINAL MODEL OF (NEXT HOUR & DAY) LOAD FORECASTING
% USING HYBRID ANALYTICAL MODEL FOR USA DATA
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear all
clc
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% calling the data
[day,month,year,hour,temp,power,dayn,daysq,modenum]=read_usaa_data('u
saa_data');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% data analyzed
data=[day,month,year,hour,Ts,Ps,dayn,daysq,modenum];
data_tr=data(1:43824,:);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
A=data_tr;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
B = zeros(size(A, 1), 1);
C = unique(A(:, 9));
C(C==0)=[];
u = 1:24;

for cx = [1 : length(C)],
    c = C(cx);
    for tx = [1 : length(u)];
        v = u(tx);
        I1 = find((A(:, 9) == c) & (A(:, 4) == v));
        B(I1) = mean(A(I1, 6));
    end
end

K=[B A(:,9) A(:,4)];
U=unique(K,'rows');

data_for=data(43825:end,:);

P90s=data_for(:,6);
R=P90s;
for i=1:length(P90s)
for j=1:length(U)
if (data_for(i,9)==U(j,2)) & (data_for(i,4)==U(j,3))
R(i)=[U(j,1)];
else

end
end
end

N=[R data_for(:,9) data_for(:,4)];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Fourier Analysis:

ts = 1; % time step
t = [1:ts:24];
fs = 1/ts; % frequency step
f=[-length(t)/2:length(t)/2-1]/(length(t)*ts); % frequency formula

Pmodes_model=[];

```

```

e=reshape(R,24,[]);

for i=1:length(e)

P1 = fft(e(:,i))/length(t);
P2=fftshift(P1);
amp=abs(P2); % amplitude
phi = angle(P2); % phase angle

ampp=amp(13:19)';
phii=phi(13:19)';

[ampp' ;phii'];

w=2*pi/24;

% structure of equation 4.6:
Pmodes_model=[Pmodes_model 0+2*(ampp(2)*cos(w*(t-
1)+phii(2))+ampp(3)*cos(2*w*(t-1)+phii(3))+ampp(4)*cos(3*w*(t-
1)+phii(4))+ampp(5)*cos(4*w*(t-1)+phii(5))+ampp(6)*cos(5*w*(t-
1)+phii(6))+ampp(7)*cos(6*w*(t-1)+phii(7))]];

end

% Now, the aim is to find next day average power that will carry the
% ac average modes model
% The used forecaster is next day Pavg forecasting using NN

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% NEURAL NETWORKS ANALYSIS
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
M=[d;m;y;dyn;dy;mode;Tsavg;Tsavg_1;Tsavg_2;Tsavg_3;Tsavg_4;Tsavg_5;Ts
avg_6;Tsavg_7;Psavg_1;Psavg_2;Psavg_3;Psavg_4;Psavg_5;Psavg_6;Psavg_7
;Psavg];

k=0;
p=M(1:end-1,1:1819+k);
% targets (outputs)
t=M(end,1:1819+k);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% normalization
[pn,ps]=mapminmax(p);
[tn,ts]=mapminmax(t);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
net=newff(minmax(pn), [5 1], {'tansig','purelin'},'trainbr');
net.trainParam.show = 50; % The result is shown at every # epoch
net.trainParam.lr = 0.05; % Learning rate used in some gradient
schemes
net.trainParam.epochs = 1000;% Max number of iterations
net.trainParam.goal = 1e-3; % Error tolerance; stopping criterion
net = init(net);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% train network
[net,tr,Y,E] = train(net, pn, tn);

```



```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% To simulate the training data
an = sim(net,pn);
% denormaliz
a = mapminmax('reverse',an,ts);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Next day average load forecasting
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

start_test=1819+k+1;
ih=6;

pt1=M(1:end-1,start_test:start_test+ih); % input for testing
ta1 = M(end,start_test:start_test+ih) ; % comparing

%model simulation
ptln = mapminmax('apply',pt1,ps);
pfln = sim(net,ptln);
pfl = mapminmax('reverse',pfln,ts);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%
P90savg_model=reshape(repmat(pfl,24,1),1,[]);
P90s_model=Pmodes_model((24*k+1:24*k+24*(ih+1)))+P90savg_model;

ta=P90s((24*k+1:24*k+24*(ih+1)));
pf=P90s_model;

e=100*(ta-pf')./ta;

mape=mean(abs(e));

subplot(211)
plot(ta1,'LineWidth',1.5);hold on
plot(pf,'-r','LineWidth',1.5);grid
legend('actualal','forecasted')
title('( a )');xlabel('hours');ylabel('Power (MW)')

subplot(212)
plot(abs(e),'b','LineWidth',1.5);hold on
plot(repmat(mape,length(e),1),'-r','LineWidth',1.5);grid
legend('absolute error','MAPE')
title('( b )');xlabel('hours');ylabel('% error')

```

## REFERENCES

- [1] Minghao Piao, Jin Hyoung Park, Heon Gyu Lee, Jin-ho Shin, Duck Jin Chai, Keun Ho Ryu, "Assessment of Temperature Sensitivity Analysis and Temperature Regression Model for Predicting Seasonal Bank Load Patterns", IEEE International Workshop on Semantic Computing and Applications, pp. 81-84, 2008.
- [2] S. A. Soliman, S. Persaud, K. El-Nagar and M. E. El-Hawary, "Application of least absolute value parameter estimation based on linear programming to short-term load forecasting," International Journal of Electrical Power and Energy systems, Vol. 19, pp. 209-216, 1997.
- [3] S.A. Soliman and Ahmad M. Al-Kandari, "Electrical Load Forecasting Modeling and Model Construction", 2010, Elsevier.
- [4] M.C. Falvo, R. Lamedica, A. Prudenzi, "Meteorological Parameters Influence for Medium Term Load Forecasting", 2006, IEEE.
- [5] Rob J. Hyndman and Shu Fan, "Density Forecasting for Long-Term Peak Electricity Demand", IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 25, NO. 2, pages 1142-1153, MAY 2010.
- [6] Simaneka Amakali, "Development of Models for Short-Term Load Forecasting Using Artificial Neural Networks", Master Thesis, Cape Peninsula University of Technology, 2008.
- [7] Fahad Al-Turki, "A Fuzzy Neural Approach For Forecasting Peak Power Demands", Journal of King Saud University, Volume 14, {Engineering Sciences (No. 1)}, pp. 29-40, 2002.

- [8] S. Alvisi, G. Mascellani, M. Franchini, and A. B'ardossy. "Water level forecasting through fuzzy logic and artificial neural network approaches", *Hydrology and Earth System Sciences*, 1107–1145, 2005.
- [9] Zeng yanfei W u yinbo,"Design of Short Term Load Forecasting model based on BP Neural network and Fuzzy Rule", *Electric Information and Control Engineering (ICEICE)*, pp 5828 – 5830, 2011.
- [10] Arash Ghanbari, Esmail Hadavandi and Salman Abbasian-Naghneh, "Comparison of Artificial Intelligence based Techniques for Short Term Load Forecasting", *Third International Conference on Business Intelligence and Financial Engineering*, pp 6-10, 2010.
- [11] S .Chenthur Pandian, K. Duraiswamy, C. Christofer Asir Rajan, N. Karangaraj "Fuzzy approach for short term load forecasting" *Electric Power System Research*, Vol 76, pp 541-548, 2006.
- [12] Kun-Long Ho, Yuan-Yih Hsu, Chih-Chien Liang and Tau-Shin Lai, "SHORT TERM LOAD FORECASTING OF TAWAN POWER SYSTEM USING A KNOWLEDGE-BASED EXPERT SYSTEM", *IEEE Transactions on Power Systems*, Vol. 5, No. 4, pp 1214-1221, November 1990.
- [13] S. Rahman, O. Hazim, "Load forecasting for multiple sites: development of an expert system-based technique", *Electric Power Systems Research*, pp 39, 161-169 1996.
- [14] K. H. Kim, J. K. Park, K. J. Hwang, and S. H. Kim, "Implementation of hybrid short-term load forecasting system using artificial neural networks and fuzzy expert systems," *IEEE Trans. Power Systems*, vol. 10,no. 3, pp. 1534–1539, 1995.

- [15] D. Srinivasan, S. S. Tan, C. S. Chang, and E. K. Chan, "Parallel neural network-fuzzy expert system for short-term load forecasting: System implementation and performance evaluation," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 1100–1106, Aug 1999.
- [16] Mohammed El-Telbany a, Fawwaz El-Karmi, "Short-term forecasting of Jordanian electricity demand using particle swarm optimization", *Electric Power Systems Research* 78, pp 425–433, 2008.
- [17] Azzam-ul-Asar, Syed Riaz ul Hassnain, and Affan Khan, "Short Term Load Forecasting Using Particle Swarm Optimization Based ANN Approach", *Proceedings of International Joint Conference on Neural Networks*, Orlando, Florida, USA, August 12-17, 2007.
- [18] Chao-Ming Huang, Chi-Jen Huang, and Ming-Li Wang, "A Particle Swarm Optimization to Identifying the ARMAX Model for Short-Term Load Forecasting", *IEEE TRANSACTIONS ON POWER SYSTEMS*, VOL. 20, NO. 2, pp 1126-1133, MAY 2005.
- [19] WANG Xuan, LV Jiake, WEI Chaofu and XIE Deti, "A Hybrid Particle Swarm Optimization Neural Network Approach for Short Term Load Forecasting", *Wireless Communications, Networking and Mobile Computing*, pp 1-5, 2008.
- [20] Rosa M de Castro Fernandez and Horacio Nilson, "Overview of Wavelet Transforms Applications in Power Systems", 14<sup>th</sup> PPSCC, Sevilla, 24-28 June, 2002.
- [21] S.J. Yao, Y.H. Song, L.Z. Zhang, X.Y. Cheng, "Wavelet transform and neural networks for short-term electrical load forecasting", *Energy Conversion & Management* 41, pp 1975-1988, 2005.

- [22] Tai Nengling, Jürgen Stenzel, Wu Hongxiao, “Techniques of applying wavelet transform into combined model for short-term load forecasting”, *Electric Power Systems Research* 76, pp 525–533, 2006.
- [23] Zidan Bashir and El-Hawary, M.E., “Short Term Load Forecasting by using Wavelet Neural networks”, *Canadian Conference on Electrical and Computer Engineering*, pp 163-166, 2000.
- [24] Introduction to regression analysis  
<http://www.saylor.org/site/wp-content/uploads/2011/11/ME205-6.1-TEXT2.pdf>
- [25] Kim, Chang II, “A study on the development and applications of Wavelet Transform Based Forecasting Models in Power Systems”, PHD Thesis, December, 2001.
- [26] Slobodan Ružić, Aca Vučković, and Nikola Nikolić, “Weather Sensitive Method for Short Term Load Forecasting in Electric Power Utility of Serbia”, *IEEE TRANSACTIONS ON POWER SYSTEMS*, VOL. 18, NO. 4, pp 1581-1586, NOVEMBER 2003.
- [27] A.M. Al-Kandari, S.A. Soliman, M.E. El-Hawary. Fuzzy short-term electric load forecasting. *Electrical Power and Energy Systems*; 26(2): pp 111–122, 2004
- [28] Amral, N. Ozveren, C.S. et al. Short Term Load Forecasting using Multiple Linear Regression. *Proc. of 42nd Int. Universities Power Engineering Conference*, Brighton, 1192-1198, 2007.
- [29] Eugene A. Feinberg, Dora Genethliou. ” *Applied Mathematics for Restructured Electric Power Systems*”, Springer US, 2005, pages 269-285.

- [30] Paras Mandal, Tomonobu Senjyu, Naomitsu Urasaki and Toshihisa Funabashi, "A neural network based several-hour-ahead electric load forecasting using similar days approach", *Electrical Power and Energy Systems* 28, pp 367–373, 2006.
- [31] YU-JUN HE YOU-CHAN ZHU JIAN-CHENG GU and CHENG-QUN YIN, "SIMILAR DAY SELECTING BASED NEURAL NETWORK MODEL AND ITS APPLICATION IN SHORT-TERM LOAD FORECASTING", *Proceedings of the Fourth International Conference on Machine Learning and Cybernetics, Guangzhou*, pp 4760-4763, 18-21 August 2005.
- [32] Jianguang Deng, and Panida Jirutitijaroen, "Short-Term Load Forecasting Using Time Series Analysis: A Case Study for Singapore", *Singapore National Research Foundation, Grant*, 2007.
- [33] Amjady, N., "Short-term hourly load forecasting using time-series modeling with peak load estimation capability," *Power Systems, IEEE Transactions on*, vol.16, no.3, pp.498-505, Aug 2001.
- [34] Espinoza, M. and et al, "Short-Term Load Forecasting, Profile Identification, and Customer Segmentation: A Methodology Based on Periodic Time Series," *IEEE Transactions on Power Systems*, vol.20, no.3, pp. 1622-1630, Aug. 2005.
- [35] Eugene A. Feinberg, Dora Genethliou. " Applied Mathematics for Restructured Electric Power Systems", Springer US, pages 391-418, 2005
- [36] Himanshu A. Amarawickramaa, Lester C. Hunt, "Electricity demand for Sri Lanka: A time series analysis", *Energy* 33, pp 724–739, 2008.
- [37] V.N. Vapnik, " The Nature of Statistical Learning Theory", NewYork, Springer Verlag, 1995.

- [38] N. Christiani and J.S. Taylor. "An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods", Cambridge University Press, Cambridge, 2000.
- [39] Chen, Bo-Juen, Chang, Ming-Wei and Chih-Jen lin, "Load forecasting using support vector Machines: a study on EUNITE competition 2001," Power Systems, IEEE Transactions on, vol.19, no.4, pp. 1821-1830, Nov. 2004.
- [40] Amit Jain and Satish.B, Integrated Approach for Short Term Load Forecasting using SVM and ANN, Proceedings of IEEE TENCON 2008, Hyderabad, India, November 18-21, 2008.
- [41] M. Mohandes, "Support Vector Machines for Short-Term Electrical Load Forecasting", International Journal of Energy Research, 26:335–345, 2002.
- [42] <http://www.timeanddate.com/calendar/?year=1988&country=1>
- [43] Neural Network Toolbox User's Guide. s.l. : The MathWorks, Inc., 2007.
- [44] <http://koti.mbnet.fi/~phodju/nenet/NeuralNetworks/NeuralNetworks.html>
- [45] M. Tarafdar Haque, and A.M. Kashtiban, "Application of Neural Networks in Power Systems and A Review", Proceedings of World Academy of Science, Engineering and Technology volume 6, pp 53-57, June 2005.
- [46] O.A. Alsayegh. "Short-Term Load Forecasting Using Seasonal Artificial Neural Networks". International Journal of Power and Energy Systems, Vol. 23, No. 3, 2003.
- [47] <http://www.imtech.res.in/raghava/ftg/Fourier-Transformation.html>

- [48] Radwan E. Abdel-Aal, "Short-Term Hourly Load Forecasting Using Abductive Networks", IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 19, NO. 1, pp 164 – 173, , FEBRUARY 2004.
- [49] AbTech Corporation, Charlottesville, VA, USA, AIM User's Manual, 1990.
- [50] S. J. Farlow, "The GMDH algorithm," in Self-Organizing Methods in Modeling: GMDH Type Algorithms, S. J. Farlow Ed. New York: Marcel-Dekker, pp. 1-24, 1984
- [51] A. R. Barron, "Predicted squared error: A criterion for automatic model selection Self-Organizing," in Self-Organizing Methods in Modeling: GMDH Type Algorithms, S. J. Farlow, Ed. New York: Marcel-Dekker, pp. 87-103, 1984.



## Vitae

- Ahmad Abdulaziz Mubaireek Al-Subhi Al-Harbi.
- Born in Bader, Madinah region, Saudi Arabia in 1982.
- Completed Bachelor of Science (Bs.c) degree in Electrical Engineering from King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia in June, 2005.
- Worked at Royal Commission of Yanbu (August, 2005 – March, 2006), Technical Yanbu College (March, 2006 – October, 2006) and Saudi Electricity Company (SEC) in Bader (October, 2006 – August, 2007).
- Joined Yanbu Industrial College in Royal Commission of Yanbu in August, 2007 to present.
- Completed Master of Science (Ms.c) degree in Electrical Engineering from KFUPM in April, 2012.
- Email: [shaheed107@yahoo.com](mailto:shaheed107@yahoo.com)