KNOWLEDGE-BASED AND STATISTICAL LOAD FORECAST MODEL DEVELOPMENT AND ANALYSIS

by

Ibrahim Said Moghram

Dissertation submitted to the Faculty of the

Virginia Polytechnic Institute and State University

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ELECTRICAL ENGINEERING

APPROVED:

Saifur Rahman, Chairman

Iaonnis M. Besieris

Robert F. Foutz

William H. Mashburn

Jaime De la Ree

December 1989

Blacksburg, Virginia

KNOWLEDGE-BASED AND STATISTICAL LOAD FORECAST MODEL DEVELOPMENT AND ANALYSIS

by

Ibrahim Said Moghram

Saifur Rahman, Chairman

ELECTRICAL ENGINEERING

(ABSTRACT)

Most of the techniques that have been applied to the short-term load forecasting problem fall within the time series approaches. The exception to this has been a new approach based on the application of expert systems. Recently several techniques have been reported which apply the rule-based (or expert systems) approach to the short-term load forecasting problem. However, the maximum lead time used for these forecasts has not gone beyond 48 hours, even though there is a significant difference between these algorithms in terms of their data base requirements (few weeks to 10 years).

The work reported in this dissertation deals with two aspects. The first one is the application of rule-based techniques to weekly load forecast. A rule-based technique is presented that is capable of issuing a 168-hour lead-time load forecast. The second aspect is the development of a comprehensive load forecasting system that utilizes both the statistical and rule-based approaches. This integration overcomes the deficiencies that exist in both of these modeling techniques.

The load forecasting technique is developed using two parallel approaches. In the first approach expert information is used to identify weather variables, day types and diurnal effects that influence the electrical utility load. These parameters and hourly historical loads are then selectively used for various statistical techniques (e.g., univariate, transfer function and linear regression). A weighted average load forecast is then produced which judiciously combines the forecasts from these three techniques. The second approach, however, is free of any significant statistical computation, and is based totally on rules derived from electric utility experts. The data base requirement for any of these approaches do not extend more

than four weeks of hourly load, dry bulb and dew point temperatures. When the algorithms are applied to generate seven-day ahead load forecasts for summer (August) and winter (February) the average forecast errors for the month come under 3%.

Acknowledgements

I would like to extend my deepest gratitude to my advisor Dr. Saifur Rahman for all his support, comments and suggestions, and guidance through the course of my dissertation research. I would also like to express my thanks to the rest of my supervisory committee: Dr. I. M. Besieris, Dr. R. F. Foutz, Mr. W. H. Mashburn, and Dr. J. De la Ree for their time and effort.

A special thanks goes to the department of Electrical Engineering and to Dr. Saifur Rahman for the financial support through the course of my Ph.D. study. A note of gratitude is due to my country, Yemen, for my education from the primary school to the graduate studies overseas.

My deep appreciation is due to my wife, , for her understanding, encouragement and support through the years of my graduate studies, and for her patience and care in looking after our two children, , who were both born during my studies at Virginia Tech. Also my appreciation goes to my father, brothers, sisters, and the rest of the family for their support though some of them could have been affected by my absence.

Finally, I would like to recognize the Large Scale Nonlinear Systems Program of the National Science Foundation for sponsoring and supporting parts of the research reported in this dissertation.

Table of Contents

INTRODUCTION 1

A REVIEW OF LOAD FORECASTING METHODOLOGIES 4

2.1 Introduction 4

2.2 Load-Forecasting Parameters 6

2.2.1 Non-weather sensitive parameters 6

2.2.2 Weather parameters 7

2.2.3 Temperature-Humidity Index (THI) 8

2.2.4 Wind Chill Index (WCI) 9

2.3 Multiple Linear Regression (MLR) 9

2.4 Stochastic Time Series (STS) 11

2.5 Exponential Smoothing (ES) 16

2.5.1 Basic exponential smoothing 17

2.5.2 Double exponential smoothing 18

2.5.3 Triple exponential smoothing 18

2.5.4 Winters method 19

2.5.5 General exponential smoothing (GES) 20

2.6 State Space and Kalman Filter 27

2.7 Other Conventional Methods 34

2.8 Rule-Based Approach 35

2.9 Summary 36

2.9.1 Model Variable Identification and Estimation 37

2.9.2 Error Analysis and Accuracy of Result 37

NEED FOR ADAPTIVE FORECASTING TECHNIQUES 41

3.1 Introduction 41

3.2 Role of Load Forecast 44

3.3 Features Required in Load Forecasting Algorithm 46

3.3.1 Adaptivity 46

3.3.2 Recursiveness 48

3.3.3 Computational economy 48

3.3.4 Robustness 49

3.4 Planned Objectives 49

3.5 Appropriateness of Rule-Based Approach. 50

3.6 Benefits from Combined Rule-Based and Statistical Approaches 53

3.7 Summary 55

EXPERT SYSTEMS AND THEIR APPLICATIONS 57

4.1 Introduction 57

4.2 Definition and Features of an Expert System 58

4.3 Need for an Expert System 59

4.4 Architecture of an Expert System 60

4.4.1 Knowledge Base 60

4.4.2 Inference Engine 60

4.4.3 Acquisition Module 62

4.4.4 Explanatory Interface 62
4.5 Characteristics of an Expert System 62
4.6 Activities of an Expert System 63
4.7 Expert Systems Applied to Power Systems 65
4.8 Programming Languages and Expert System Shells 67
4.9 Rule-Based Programming 68
4.10 Summary 68

TIME SERIES APPROACH TO LOAD FORECASTING 69
5.1 Introduction 69
5.2 Classes of Stochastic Time Series Processes 70
5.3 Modeling 71
5.3.1 The Autoregressive (AR) process 71
5.3.2 The Moving-Average (MA) process 73
5.3.3 The Autoregressive Moving-Average (ARMA) process 74
5.3.3 The Autoregressive Integrated Moving-Average (ARIMA) process 75
5.3.4 Seasonal processes 76
5.3.5 Transfer function modeling 77
5.4 The Box-Jenkins Methodology 79
5.4.1 Identification 79
5.4.2 Estimation 81
5.4.3 Diagnostic checking 82
5.4.4 Over-fitting 82
5.5 Summer Load-Forecast Models 82
5.6 Results from Time Series Modeling 104
5.7 Conclusion 107

EXPERT SYSTEMS APPROACH TO LOAD FORECASTING 109

6.1 Introduction 109
6.2 Rule-Based Load Forecasting 110
6.3 Forecast Program 112
6.3.1 Data base 113
6.3.2 Selection of data for forecasting 113
6.3.3 Load forecast calculation 114
6.4 Results and Discussions 118
6.4.1 The 168-hour lead time hourly load prediction 118
6.4.2 The 7-day lead-time daily peak prediction 127
6.5 Conclusion 127

EVALUATION OF SHORT-TERM LOAD FORECASTING TECHNIQUES 135
7.1 Introduction 135
7.2 Implementation of the Algorithms 136
7.3 Multiple Linear Regression (MLR) 136
7.4 Stochastic Time Series (STS) 138
7.5 General Exponential Smoothing (GES) 141
7.6 State Space Approach (SS) 142
7.7 Knowledge-Based Expert System (KBES) 145
7.8 Comparative Summary of Results 147
7.9 Conclusion 150

AN INTELLIGENT LOAD FORECASTING SYSTEM 152
8.1 Introduction 152
8.2 Objective of the Load Forecasting System 153
8.3 Load Forecasting System Structure 154
8.3.1 Data base 154
8.3.2 Load forecast model 156

8.3.3 Input/Output facilities 156
8.4 Development of the Load Forecasting System 157
8.5 Knowledge Acquisition 157
8.6 Knowledge-Base 159
8.6.1 Load process 161
8.6.2 Weather process 163
8.6.3 Load-weather relationships 164
8.6.4 Load modeling 166
8.6.5 Performance evaluation 168
8.6.6 Uncertainty handling 170
8.6.7 Energy management 171
8.7 Summary 172

PERFORMANCE EVALUATION OF THE LOAD FORECASTING SYSTEM 173
9.1 Introduction 173
9.2 Simulation 174
9.2.1 Power method 176
9.2.2 Energy method 177
9.3 Modeling Evaluation 179
9.3.1 Daily prediction 180
9.3.2 Weekly prediction 188
9.4 Adaptive Weekly Predictions 190
9.4.1 Statistical modeling 191
9.4.2 Weighted Averaging 192
9.4.3 Rule-based modeling 193
9.5 Results 193
9.5.1 Statistical modeling 195
9.5.2 Rule-based modeling 203

9.6 Conclusions 203

CONCLUSIONS AND RECOMMENDATIONS 209

10.1 Recommendations. 212

REFERENCES 214

TIME SERIES WEEKLY LOAD PREDICTIONS 220

WEEKLY LOAD FORECAST ERROR DISTRIBUTIONS 227

ASSUMPTIONS USED FOR DIFFERENT LOAD MODELING TECHNIQUES 236

SAMPLES OF LOAD MODELS 238

Univariate analysis (UV) 238

Transfer function anlysis (TF) 239

Linear regression analysis (LR) 240

DAILY PEAK PREDICTIONS USING ALL MODELS 242

Vita 273

List of Illustrations

Figure 1. Load Forecast as an Integral Part of Utility Operations. (Source: Ref. 85) ... 43

Figure 2. Components of an Expert System. ... 61

Figure 3. Description of a Time Series as the Output of Linear Filter Whose Input is a White Noise. ... 72

Figure 4. Transfer Function Load Modeling ... 78

Figure 5. Procedure of the Box and Jenkins Methodology. ... 80

Figure 6. The Autocorrelation Function (ACF) of the Summer Hourly Load Time Series, y(t) ... 84

Figure 7. The Autocorrelation Function (ACF) of the Summer Hourly Load Time Series (a) ... 85

Figure 8. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Summer Hourly Load Time Series, ... 86

Figure 9. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Noise Series, a(t). ... 89

Figure 10. The Actual and Forecasted Hourly Load Data for August 1-7 1983 ... 90

Figure 11. The Autocorrelation Function (ACF) of the Summer Hourly Input Time Series, x(t) ... 92

Figure 12. The Autocorrelation Function (ACF) of the Summer Hourly Input Time Series (a) ... 93

Figure 13. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Summer Hourly Input Time Series, ... 94

Figure 14. The Autocorrelation Function (ACF) and the Partial Correlation Function (PACF) of the noise series, ... 97

Figure 15. Actual and Forecasted Hourly Input (Dry Bulb Temperature) for 1-7 August 1983. 98

Figure 16. Crosscorelation Function (CCF) Between the "Prewhitened" Input and the Transformed Output , ... 100

Figure 17. The Autocorrelation Function (ACF) and the Partial Correlation Function (PACF) of the noise series, n(t) 102

Figure 18. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Noise Series, a(t). 103

Figure 19. Actaul and Forecasted (TF model) Hourly Load Data for 1-7 August 1983 (Using Forecasted Input Data) 105

Figure 20. Actaul and Forecasted (TF model) Hourly Load Data for 1-7 August 1983 (Using Actual Input Data) 106

Figure 21. Actaul and Forecasted Summer Load (1-7 August 1983) Using 20-hour Lag Time Effect for Temperature Variable 128

Figure 22. Actaul and Forecasted Summer Load (8-14 August 1983) Using 20-hour Lag Time Effect for Temperature Variable 129

Figure 23. Actaul and Forecasted Summer Load (15-21 August 1983) Using 20-hour Lag Time Effect for Temperature Variable 130

Figure 24. Actaul and Forecasted Summer Load (22-28 August 1983) Using 20-hour Lag Time Effect for Temperature Variable 131

Figure 25. Actaul and Forecasted Summer daily Peak Load (1-31 August 1983) Using 20-hour Lag Time Effect for Temperature Variable 133

Figure 26. Structure of a Load Forecasting System 155

Figure 27. Components of the Load Forecasting System 158

Figure 28. Knowledge-Base of the Load Forecasting System 160

Figure 29. Actual and Forecasted (seasonal ARIMA) Hourly Load Data for Fall Model (17-23 October 1983) 221

Figure 30. Actual and Forecasted (seasonal ARIMA) Hourly Load Data for Winter Model (7-13 February 1983) 222

Figure 31. Actual and Forecasted (TF Model) Hourly Load Data for Winter Model (7-13 February 1983) Using Forecasted Input values 223

Figure 32. Actual and Forecasted (TF Model) Hourly Load Data for Winter Model (7-13 February 1983) Using Actual Input Values 224

Figure 33. Actual and Forecasted (seasonal ARIMA) Hourly Load Data for Spring Model (25 April to 1 May 1983) 225

Figure 34. Actual and Forecasted (TF ARIMA) Hourly Load Data for Spring Model (25 April to 1 May 1983) Using Forecasted Input values 226

List of Tables

Table 1. Summary of Various Characteristics of Five Load Forecasting Techniques . . . 38

Table 2. Summary of Error Analysis for Five Load Forecasting Techniques 40

Table 3. Estimates of the Summer Hourly Load Seasonal ARIMA Model Parameters . 87

Table 4. Estimates of the Summer Model Input Parameters 96

Table 5. Estimates of the Summer Hourly Load TF Model Parameters 101

Table 6. Average Absolute Percent Forecast Error for Four Seasons 108

Table 7. Addative Correction Factors Coefficients for the Summer Model 119

Table 8. One-Week Lead Time Absolute Load Forecast Percent Error (w.r.t. Hourly Load) for Different Lag Time Temperature Effect 121

Table 9. One-Week Lead Time Absolute Load Forecast Percent Error (w.r.t. Daily Peak) for Different Lag Time Temperature Effect 122

Table 10. One-Week Lead Time Percent Forecast Error Statistics for August 1983 for Different Lag Time Temperature Effect 123

Table 11. One-Week Lead Time Absolute Hourly MW Forecast Error Statistics for Different Lag Time Temperature Effect 124

Table 12. One-Week Lead Time Absolute Load Forecast Percent Error (w.r.t. Hourly Load) for Different Lag Time Temperature Effect 125

Table 13. One-Week Lead Time Absolute Load Forecast Percent Error (w.r.t. Daily Peak) for Different Lag Time Temperature Effect 126

Table 14. Absolute MW Daily Peak Load Forecast Error Statistics for Different Lag Time Temperature Effect 132

Table 15. Weekday MLR Summer Model Parameter Estimates for Different Time Intervals of the Day 139

Table 16. Weekday MLR Winter Model Parameter Estimates for Different Time Intervals of the Day 140

Table 17. General Exponential Smoothing Summer and Winter Model Estimates 143

Table 18. Forecast Percent Error for Summer Using the Five Load Forecasting Algorithms 148

Table 19. Forecast Percent Error for Winter Using the Five Load Forecasting Algorithms 149

Table 20. Daily Peak Forecast Error Using Hourly Load Model Predictions 181

Table 21. Daily Peak Forecast Error Using Daily Peak Load Model 182

Table 22. Daily Peak Forecast Error Using Daily Energy Prediction and Actual Load Factor 183

Table 23. Daily Peak Forecast Error Using Daily Energy Prediction and Average Load Factor 184

Table 24. Daily Peak Forecast Error Using Daily Energy and Load Factor Predictions . 185

Table 25. Weighted Averaging Values for the Statistical Models 194

Table 26. Forecast Errors for February Using Univariate Models 197

Table 27. Forecast Errors for August Using Univariate Models 198

Table 28. Forecast Error for February Using Transfer Function Models 199

Table 29. Forecast Error for August Using Transfer Function Models 200

Table 30. Forecast Error for February Using Regression Models 201

Table 31. Forecast Error for August Using Regression Models 202

Table 32. Percentage Errors for Various Techniques and Models 204

Table 33. Forecast Error for February Using Weighted UV, TF, and LR Models 205

Table 34. Forecast Error for August Using Weighted UV, TF, and LR Models 206

Table 35. Forecast Error for August Using the Expert System Model 207

Table 36. One-Week Lead Time Absolute Percent Forecast Error (wrt Hourly Load) Distribution with 12-hour Lag Time Temperature Effect 228

Table 37. One-Week Lead Time Absolute Percent Forecast Error (wrt Hourly Load) Distribution with 16-hour Lag Time Temperature Effect 229

Table 38. One-Week Lead Time Absolute Percent Forecast Error (wrt Hourly Load) Distribution with 20-hour Lag Time Temperature Effect 230

Table 39. One-Week Lead Time Absolute Percent Forecast Error (wrt Hourly Load) Distribution with 24-hour Lag Time Temperature Effect 231

Table 40. One-Week Lead Time Absolute Percent Forecast Error (wrt Daily Peak) Distribution with 12-hour Lag Time Temperature Effect 232

Table 41. One-Week Lead Time Absolute Percent Forecast Error (wrt Daily Peak) Distribution with 16-hour Lag Time Temperature Effect 233

Table 42. One-Week Lead Time Absolute Percent Forecast Error (wrt Daily Peak) Distribution with 20-hour Lag Time Temperature Effect 234

Table 43. One-Week Lead Time Absolute Percent Forecast Error (wrt Daily Peak) Distribution with 24-hour Lag Time Temperature Effect 235

Table 44. One-Day Lead Time Daily Peak Forecast Error Using Hourly Load Univariate Model 243

Table 45. One-Day Lead Time Daily Peak Forecast Error Using Hourly Load Transfer Function Model with Actual Future Input Data 244

Table 46. One-Day Lead Time Daily Peak Forecast Error Using Hourly Load Transfer Function Model with Predicted Future Input Data 245

Table 47. One-Week Lead Time Daily Peak Forecast Error Using Hourly Load Univariate Model 246

Table 48. One-Week Lead Time Daily Peak Forecast Error Using Hourly Load Transfer Function Model with Actual Future Input Data 247

Table 49. One-Week Lead Time Daily Peak Forecast Error Using Hourly Load Transfer Function Model with Predicted Future Input Data 248

Table 50. One-Day Lead Time Daily Peak Forecast Error Using Daily Peak Univariate Model 249

Table 51. One-Day Lead Time Daily Peak Forecast Error Using Daily Peak Transfer Function Model with Actual Future Input Data 250

Table 52. One-Day Lead Time Daily Peak Forecast Error Using Daily Peak Transfer Function Model with Predicted Future Input Data 251

Table 53. One-Week Lead Time Daily Peak Forecast Error Using Daily Peak Univariate Model 252

Table 54. One-Week Lead Time Load Forecast Error Using Daily Peak Load Transfer Function Model with Actual Future Input data 253

Table 55. One-Week Lead Time Daily Peak Forecast Error Using Daily Peak Transfer Function Model with Predicted Future Input Data 254

Table 56. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Univariate Model and Actual Load Factor 255

Table 57. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Actual Input Data and Actual Load Factor 256

Table 58. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Predicted Input Data and Actual Load Factor 257

Table 59. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Univariate Model and Actual Load Factor 258

Table 60. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Actual Input Data and Actual Load Factor 259

Table 61. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Predicted Input Data and Actual Load Factor 260

Table 62. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Univariate Model and Average Load Fcator 261

Table 63. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Models with Actual Input Data and Average Load Factor 262

Table 64. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Predicted Input and Average Load Factor Input Data .. 263

Table 65. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Univariate Model and Average Load Fcator 264

Table 66. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Models with Actual Input Data and Average Load Factor 265

Table 67. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Models with Predicted Input Data and Average Load Fcator 266

Table 68. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Univariate Models 267

Table 69. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Transfer Function Models with Actual Input Data 268

Table 70. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Transfer Function Models with Predicted Input Data 269

Table 71. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Univariate Models 270

Table 72. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Transfer Function Models with Actual Input Data 271

Table 73. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Transfer Function Models with Predicted Input Data 272

Chapter I

INTRODUCTION

Load forecasting is a central and an integral process in the operation and planning of electric power systems. Therefore, accurate load forecasts are always needed for the successful operation of these systems. Many techniques have been investigated to solve the problem of load forecasting in the last 15 to 20 years. These techniques have been classified depending on the area of application into long, medium, and short term load forecasting. Long-term load forecasting is necessary for system planning such as to expand the system capability in order to meet the expected long-term growth in demand. Medium-term load forecasting is necessary for scheduling of fuel supplies, scheduling of maintenance operations, and planning for inter-utility power transfer. Short-term load forecasting is necessary in the daily operations such as unit commitment, energy transfer scheduling, and load dispatch. Besides, the short-term load forecasting is necessary for the coordination of the energy management programs with the system resources [1].

Almost all the existing techniques that have been used to solve the problem of load forecasting fall in the time series approaches [2]. Such approaches can give results with accuracies as high as 2% absolute average error (w.r.t. peak load) for short lead times (up to 24 hours). Accuracies decrease as the lead time increases. However, such algorithms require, for the statistical analysis, huge historical data bases. These data bases could be as large as 2 or 3 years in depth. Other techniques such as pattern recognition may require larger data bases which could go up to 10 years [3]. There are of course other techniques which could require smaller data bases such as correlation, regression, exponential smoothing, state-space and Kalman filter, and others. However these approaches are not as popular in their application to the load forecast problem as the time series approach.

Recently, a new technique based on the application of expert systems to the problem of load forecast has been introduced by Rahman and Bhatnagar. Rahman and Bhatnagar [2,4] proposed and applied a knowledge-based algorithm for short term load forecasting. They tested their method against some existing statistical methods. They developed an algorithm for the six-hour load forecast and another algorithm for the 24-hour load forecast. Such algorithms were developed "based on the logical and syntactical relationships between the weather and prevailing daily load shapes" [2].

In the light of the current state of the art of load forecasting the direction of this research was to pursue the investigation of the short-term load forecasting up to 168-hour lead time predictions. Therefore, the direction of this research is intended to proceed in the investigation of both statistical and rule-based approaches to the development of load forecasting algorithms. These algorithms would include a short-term forecast for hourly load demand up to 168-hour lead-time and a daily peak load forecast up to 7-day lead time. This algorithms would be integrated under an intelligent load forecasting system.

The work proposed in this dissertation research starts by a study of the existing statistical and knowledge-based load forecasting techniques as covered in Chapter 2. This includes discussion on the structure of the load forecasting problem and the different methods that have been used in approaching this problem. Through this study, the need for an adaptive short-term load forecasting technique has been identified. The use of an adaptive load forecasting technique, based on both the statistical and rule-based approaches, is presented in chapter 3. This includes the argument why it is necessary to investigate both the conventional techniques as well as the rule-based approaches. Thus it is argued that the logical way to proceed for developing load forecasting algorithms, that are adaptive to changing conditions, is the implementation of knowledge based systems which include both the conventional and rule rule-based approaches. This is followed by Chapter 4 which gives a brief presentation on expert systems and their applications to power systems. Following this a discussion on the time series approach to load forecasting with improved models for weekly load prediction is presented in chapter 5. This is followed in chapter 6 by an implementation of rule-based (expert system) techniques to the 168-hour lead time load forecast prediction. Analysis and evaluation of this technique is also presented in this chapter. In chapter 7, short-term (24-hour lead time) load forecast models are developed using several statistical techniques. The predictions of these load forecast models have been compared with the predictions produced by a model that is completely based on a rule-base approach. Evaluation of these techniques are presented as applied to the same data base. In chapter 8, an intelligent load forecasting system is proposed. This system integrates both the statistical and rule-based approaches under a knowledge-based system. This is followed by an evaluation of the performance of this load forecasting system as presented in chapter 9. Finally, conclusions and recommendations that have resulted from this study are presented in chapter 10.

Chapter II

A REVIEW OF LOAD FORECASTING METHODOLOGIES

2.1 Introduction

Load forecast has been an important process in the planning and operation of electric utilities. Therefore, many techniques and philosophies have been investigated to tackle this problem in the last two decades. These techniques and philosophies are often different in nature and may implement different engineering considerations and economic analyses.

The IEEE load forecasting working group has published, in two phases, a documentary bibliography on load forecasting. The first bibliography (PHASE I) has covered general philosophies of load forecasting [5]. The second bibliography (PHASE II) has focused on the economic issues of load forecasting [6]. The most recent review is reported by Gross and Galiana [7] in 1987 where the authors have reviewed various short-term load forecasting techniques that have been proposed or in use today. There are additional publications that have reviewed load forecasting. One of these is the work of Bunn [8] which has reviewed the short-term load forecasting procedures in the electricity supply industry. In another work Bunn and Farmer [1] have also reviewed and discussed the forecasting techniques that have been applied in the electric power industry. Another work by Fildes [9] has covered the explorative models for quantitative forecasting. An early review of the techniques for predicting load demands in the electric supply industry was reported by Matthewman and Nicholson [10]. In another paper Abu El-Magd and Sinha [11] have reviewed the short-term load demand modeling and forecasting. Engle and Goodrich [12] have discussed the use of seven different forecasting models to calculate one-month to five years of monthly electricity sales. Even though the targeted application of this report is different from the focus of this research, which is short-term (one hour up to one week lead time) load forecasting, the review of statistical techniques there is useful.

This chapter presents a review of the most widely applied load forecasting methodologies. In particular, those modeling techniques that have been applied to short and medium-term load forecasts. The review includes the following load forecasting methodologies:

- Multiple Linear Regression
- Stochastic Time Series
- Exponential Smoothing
- State Space and Kalman Filter
- Other Conventional Methods
- Rule-Based Approach

The review is started by an explanation of the load forecast model parameters as covered in Section 2.2. Next, discussions of the previously mentioned forecasting methodologies are given in Sections 2.3 through 2.8. Each methodology is reviewed by an explanation of its load-forecast model followed by a summary of various applications of this methodology. This is followed by a summary conclusion about the advantage and/or disadvantage of the reviewed methodology along with the range of its prediction applicability. An overall summary of these techniques is presented in Section 2.9.

2.2 Load-Forecasting Parameters

In the load forecasting problem, the number of variables or parameters which are needed to build the load-forecasting model varies depending on the philosophy and the techniques used in approaching the problem. For example, weather information may or may not be included with the recent load information to build the load-forecasting model. Besides, if weather information is included, range of the selected variables may differ from one method to another. Generally, in this section, the load forecasting parameters are divided into non-weather type parameters and weather type parameters.

2.2.1 Non-weather sensitive parameters

The non-weather type parameters may include the following [2]:

1. SEASON OF THE YEAR: This means that each season may have its own "logic" in the process of load forecasting. For example, in the summer as the (weather) temperature rises the load demand increases; while in the winter, as the (weather) temperature rises the load demand decreases.

2. SEASONAL LOAD SHAPE: This means that for each season, there is a specific load shape. For example, in the summer the load curve has one peak occurring in the late afternoon; while in the winter, the load curve has two peaks one in the morning and the other in the evening.

3. DAY-OF-THE WEEK: This means that the seasonal load shapes are more similar for the same days of the week. For example, the load shape for Tuesday resembles the previous Tuesday more than that of the previous Monday. Special days such as holidays are excluded and have to be considered separately.

2.2.2 Weather parameters

There are many weather parameters that may be selected in building load forecasting model. These selected parameters may not be the same for each load forecasting method. Some methods may implement more parameters than other methods, as some parameters may be more significant than other parameters. This significance may also vary from one season to another. These weather variables are needed in two modes; historical mode and forecast mode. In the historical mode, weather information about the day of forecast and previous days, depending on the sufficient depth for the estimation process, are needed to estimate the load-forecast model parameters. In the forecast mode, weather information is needed to issue the load forecasts using the model parameter estimates that have been evaluated using the historical mode. The weather variables may include:

- Dry bulb temperature,
- Wet bulb temperature,
- Dew point temperature,
- Relative humidity,
- Wind speed,
- Wind direction, and
- Sky cover.

These weather variables might be needed in hourly intervals if the forecast is required on an hourly basis. Some of these weather variables could be used in defining more than a variable in the load-forecast model. For example, along with the dry bulb temperature variable, other variables such as maximum, minimum, and average values for this dry bulb temperature may be needed in the load-forecast model. Other weather variables could also be expressed as a combination of more than a single variable such as the Temperature Humidity Index (THI) and Wind Chill Index (WCI) if such combination proved to be beneficial.

2.2.3 Temperature-Humidity Index (THI)

In the summer, many factors affect the air conditioning load. These include temperature difference between the human body and the surroundings, humidity of the surroundings, wind speed, and thermal radiation. Among these factors, the temperature and humidity have major effects. Therefore, in order to see the effect of both temperature and humidity together a variable combining them has been designed. This variable gives an indication about the equivalent heat stress or discomfort in the summer. This variable is called the Temperature-Humidity Index (THI) and is expressed by:

$$\begin{aligned} THI &= 0.55T + 0.2Td + 17.5 \\ THI &= 0.4(Td + Tw) + 15 \\ THI &= Td - (0.55 - 0.55RH)(Td - 58) \end{aligned} \tag{2.1}$$

where,

T = Temperature in degrees Fahrenheit.

Td = Dew point in degrees Fahrenheit.

Tw = Wet bulb temperature in degrees Fahrenheit.

RH = Relative humidity in percent.

2.2.4 *Wind Chill Index (WCI)*

In the winter, many factors affect the heating load. These include the surrounding temperature, wind speed, and wind direction. The effect of combining both the surrounding temperature and the wind speed can be combined into a single variable. The designed variable gives an indication about the discomfort in the winter due to the surrounding temperature and wind speed. This variable is called the Wind Chill Index (WCI) and is expressed by:

$$WCI = 33 - (10.45 + 10\sqrt{v} - v)(33 - T)/22.04 \tag{2.2}$$

where,

WCI = Wind chill equivalent temperate in degrees Celsius.

v = Wind speed in m/sec.

T = Temperature in degrees Celsius.

2.3 Multiple Linear Regression (MLR)

In this method, the load is found in terms of explanatory variables such as weather and non-weather variables which influence the electrical loads. These explanatory variables are found on the basis of correlation analysis.

The multiple linear regression model of the load can be written in the form:

$$y(t) = a_0 + a_1X_1(t) + \dots + a_nX_n(t) + a(t) \tag{2.3}$$

where,

y(t) = electrical load

$x_1(t) \ldots, x_n(t)$ = Explanatory variables correlated with y(t).

a(t) = a white noise

$a_0, a_1, \ldots, a_n$ = regression coefficients.

The regression coefficients are usually found using the least-square estimation technique. Statistical tests such as the F-statistic tests are performed to determine the significance of these regression coefficients. The t-ratios resulting from these tests determine the significance of each of these coefficients.

This method and the applicable algorithms are explained in many statistical books and published works such as [13,14] and others.

The application of this method to the load forecast problem was first conducted by Davis [15]. In his work, Davis has analyzed the load-weather relationship.

Heinemann et. al. [16] used this method to study the relationship between the summer load and the summer weather. They modeled the daily peak load (DPL) as:

$$DPL = B + CDF \times (WV) \tag{2.4}$$

where,

DPL = daily peak load

B = basic load

CDF = cooling demand factor

WV = weather sensitive load

Corpening et. al. [17] have expanded the work of Heinemann et. al. [16] by accounting for different weather variable functions. They have incorporated a nonlinear function of dew point temperature and weighted dry bulb temperature (DBT) from the coincident and previous three days DBT and another linear function combining wind speed and cloud coverage.

Stanton and others [18,19] used an exponentially weighted regression for forecasting medium-range and long-range load demand respectively. In their modeling the weather induced demand D_w is expressed as:

$$D_W = K_S(T - T_S) \qquad T > T_S$$

$$D_W = 0 \qquad T_W \leq T \leq T_S$$

$$D_W = K_W(T - T_W) \qquad T < T_W \tag{2.5}$$

where T = weather variable

The parameters K, K_w, T_s, and T_w are to be identified from historical load and weather data.

The success of the MLR method relies heavily on the knowledge of many factors; such as, geographical distribution of loads and weights of residential, commercial, and industrial loads relative to each other. The accuracy of the MLR method results is highly dependent on the assumptions of the model at the beginning of the analysis. This method has mostly been applied to the medium and long term load forecasts.

2.4 Stochastic Time Series (STS)

This method is the most popular approach that has been applied and is still being applied to forecasting load demand in the electric power system industry. The theory of stochastic time series is discussed in some depth in chapter 5. Therefore, discussions here will be limited to the techniques and algorithms that have been proposed and applied to the load forecast problem.

Weiner [20] was the first to develop this technique to model stationary time series. He has modeled stationary time series as the output of a linear filter whose input was a white noise. This idea was extended later by Whittle [21], and Box and Jenkins [22] to a special class of nonstationary time series by means of using a finite linear transformation.

The general model for a seasonal univariate time series model can be written in the form:

$$\Phi(B^s)\phi(B)\nabla^d\nabla_s^D y(t) = \Theta(B^s)\theta(B)a(t). \tag{2.6}$$

where,

y (t)	=	load series
$\Phi(B^s)$	=	seasonal polynomial of order P
ϕ (B)	=	polynomial of order p
$\Theta(B^s)$	=	seasonal polynomial of order Q
θ (B)	=	polynomial of order q
∇^d	=	difference operator of order d
∇_s^D	=	seasonal difference operator of order D
a(t)	=	a white noise

The previous modeling does not account for the effect of weather variables. Such an effect can be accounted for by using the transfer function modeling of time series as developed by Box and Jenkins [22]. This transfer function modeling can be expressed as:

$$y(t) = \frac{\omega(B)}{\sigma(B)}\, x(t-b) + n(t) \tag{2.7}$$

where,

ω (B)	=	polynomial of order r.
σ (B)	=	polynomial of order s.
x (t-b)	=	weather variable leading the response by b time intervals.
n (t)	=	a non-white noise series.

The noise series can be modeled as a seasonal or nonseasonal ARIMA process using the expression of equation 2.6.

There has been extensive work done for applying time series approach to the load forecast problem. Many techniques have been developed for identification and estimation of time series for off and on-line applications. A summary of these works are presented in this review.

Stanton et. al. [18,23] and Gupta [24] have applied the seasonal autoregressive moving-average (ARMA) model described by equation 2.6 to forecast medium and long-range load demand of a power system. These developed algorithms were applied for off-line forecasts.

Keyhani et. al. [25,26] have modified the previous techniques to work for on-line applications. This has been achieved by implementing a recursive estimation algorithm capable of discarding the effect of the oldest observation and accounting for the effect of new observation. Such an algorithm has been developed by Kashyap and Rao [27]. The selection of the orders p and q of the ARMA process is based on fixing a value for q, then searching for a p value below a prespecified value denoted by p^*. This process is started from zero value of q up to a prespecified value denoted by q^* [11].

Keyhani et. al. [28] have proposed another method for determining the p and q orders of an ARMA process. This has been done by assuming different ARMA models. Then, the one resulting in the minimum mean square error predication was chosen for forecasting.

Hagan et. al. [29,30] have used the seasonal ARIMA model expressed by equation 2.6 to forecast load demand up to four-hour lead time. For estimating the parameters of the process they have used an algorithm developed by Marquart [31] for least square estimation [11]. Hagan et. al. [30] have compared the transfer function (TF) model described by equation (2.7) to the seasonal ARIMA expressed by equation (2.6). They have found that the TF model results in a slightly better forecast.

In another work, Hagan et. al. [32] have used a technique called a recursive on-line maximum likelihood estimation procedure to update the process parameters [11]. This technique was based on a similar technique developed by Gertler et. al. [33].

Lately, Hagan et. al. [34] have proposed a third order polynomial to relate the daily peak temperature to the daily peak load. Instead of using the temperature as an input in the Box and Jenkins TF model [22] (equation 2.7), they have used a transformed form of this temperature value using the third order polynomial. This new modeling approach for the input has resulted in a more accurate forecast.

Vemuri et. al. [35,36] have used the ARMA model expressed by equation (2.6). They proposed a sequential least square estimator to identify the orders of the process. This is achieved by identifying an infinite order for the autoregressive (AR) model representing the process. This finite order model is then used to find an equivalent ARMA model with finite AR and MA orders. This approach of identification was claimed to lead to better results compared to the Box and Jenkins methodology. The algorithms developed were applied for on-line forecasting. Such algorithms were claimed to require little intervention by the operator where the load-forecast model needs to be revised.

Nelson and Vemuri [37] have performed an extensive analysis using the techniques proposed in [35,36]. In addition to this work, they have proposed a procedure for incorporating the temperature as a variable so that the accuracy of the forecasts can be improved. Forecast results of the proposed methodologies were claimed to show a significant improvement over those forecast results obtained using the Box and Jenkins methodology [22].

Abu-Hussein et. al. [38] have proposed two algorithms for on-line modeling and forecasting of load of a multinode power system. The models used in these algorithms are individual bus loads that are strongly dependent on weather information. The first algorithm has implemented a multivariable time series model. The order of this model and the estimates of its parameters are determined systematically based on a criterion known as the Akaikes Information Criterion (AIC) [39]. The other algorithm has implemented a state variable formulation. The estimates of the parameters and the states of the model are obtained using a combined recursive least-squares and adaptive Kalman filtering procedures.

Irisarri et. al. [40] have proposed an on-line load forecasting algorithm implementing the Generalized Least-Square Estimation approach for evaluating the load parameters estimates. The estimates provided using this approach were unbiased. This algorithm has been designed to be implemented for energy control centers with a capability of issuing forecasts up to 24-hour lead time.

Goh et. al. [41] have conducted a comparative study for short-term load forecasting of energy and peak power demand. The study is aimed at evaluating the performance of different forecasting approaches. This has been conducted in terms of both data characterization adequacy and data behavior projection. A method for selecting the best forecast model is presented. This method is based on the amount of the change of the mean square errors (MSE) in the load forecast. The model with the least increase in the change of the MSE as the forecast progresses can be selected for producing the forecasts.

Goh et. al. [42] have presented a statistical forecasting approach of daily peak power demand. This approach was based on the Box and Jenkins methodology. Peak loads for the different substations are obtained separately. The total peak demand is then found as a linear combination of these individual models.

Rajurkar et. al. [43] have developed a stochastic modeling and analysis methodology called data-dependent systems (DDS). They have applied this methodology to short-term load forecasting. They claimed that the difficulty of trial and error of most applied techniques were circumvented using the DDS by the successful fitting of higher models for the data. They have also indicated that such methodology can be used on a microcomputer as the model order was small and only the recent data were needed to be retained in the memory. The forecast results using one week of the summer data in 1983 had a maximum error of 10 percent at a peak hour. They have proposed to extend their work to the multivariate DDS modeling by including temperature and humidity; thus hoping for an improvement in the load forecast accuracy.

There are some other research that have used the stochastic time series approach. These are reported by Abu-Almagd et. al. [11] which include the works of Meslier [44], Uri [45], Liang et. al. [46], Van Meeteren et. al. [47], and De Matino et. al. [48].

The popularity of the stochastic time series approach indicates its ability to meet the general needs in the industry at present. Although most of this research is based on load data only, there are others which are able to account for weather variables such as temperature by means of the transfer function modeling as seen in Box and Jenkins [22]. A drawback in many of the proposed algorithms is the unsuitability for on-line applications as a result of the lack of an updating mechanism for the model parameters. Other techniques were proposed to overcome this problem by implementing some recursive procedures so that the model parameters can be updated to make the algorithm suitable for on-line applications. However, the implementation of the updating mechanism has shown to be effective only when the model parameters are changing slowly. Most of the proposed techniques using this methodology have been applied to the short-term load forecasting problem.

2.5 Exponential Smoothing (ES)

Exponential smoothing techniques are special cases from time series autoregressive moving-average (ARMA) processes modeling but with imposed particular restriction. A common characteristic among these techniques is represented by the procedure for weighting the data observations. The new data observations are weighted more heavily than old data observations. Discussion of these techniques are covered in this section starting from the simple exponential smoothing model.

2.5.1 Basic exponential smoothing

This model can be derived for a time series sequence of x(t), x(t-1), x(t-2), ... as given in [13] as:

$$S^{[1]}(t) = \alpha X(t) + (1-\alpha)S^{[1]}(t) \tag{2.8}$$

(t-1)

where,

$S^{[1]}(t)$ = new estimate

X(t) = new data

$S^{[1]}(t-1)$ = previous data

α = smoothing constant , $0 < \alpha < 1$

A cascade expansion for equation 2.8 yields the following form:

$$S^{[1]}(t) = \alpha X(t) + \alpha(1-\alpha)X(t-1) + \ldots\ldots + (1-\alpha)^t S^{[1]}(0) \tag{2.9}$$

where,

$S^{[1]}(0)$ = the initial estimate

Usually the initial estimate is found by averaging past observations of the process. The smoothing constant α is established by trial procedure. The criterion for this procedure could be set as: the smoothing constant α is chosen such that the root mean square error (RMSE) of the process is minimum.

2.5.2 *Double exponential smoothing*

When the data has a linear trend, a double exponential smoothing statistic $S^{[2]}(t)$ has to be used. This smoothing statistic is expressed as

$$S^{[2]}(t) = \alpha S^{[1]}(t) + (1-\alpha)S^{[2]}(t) \tag{2.10}$$

The model for forecasting future demand when linear trend exists is written as.

$$y(t+T) = a(t) + b(t+T) \tag{2.11}$$

where,

T = Lead time period from the present time, t.

The coefficients a(t) and b(t) are found as follows:

$$a(t) = 2S^{[1]}(t) - S^{[2]}(t) \tag{2.12}$$

$$b(t) = \frac{\alpha}{1-\alpha}[S^{[1]}(t) - S^{[2]}(t)] \tag{2.13}$$

The initial estimates for $S^{[1]}(0)$ *and* $S^{[2]}(0)$ have to be determined along with the value of the smoothing constant α .

2.5.3 *Triple exponential smoothing*

When the trend is changing so that curvature characteristics exist, a third exponential statistic $S^{[3]}(t)$ has to be used. This smoothing statistic is expressed as:

$$S^{[3]}(t) = \alpha S^{[2]}(t) + (1-\alpha)S^{[3]}(t) \tag{2.14}$$

The model for a forecasting series with curvature characteristics is expressed in quadratic form as:

$$y(t+T) = a(t) + b(t).T + c(t).T^2 \tag{2.15}$$

where,

$$a(t) = 3S^{[1]}(t) - 3S^{[2]}(t) + S^{[3]}(t) \tag{2.16}$$

$$b(t) = \frac{\alpha}{2(1-\alpha)^2}[(6-5\alpha)S^{[1]}(t) - 2(4-3\alpha)S^{[2]}(t) + (4-3\alpha)S^{[3]}(t)] \tag{2.17}$$

$$c(t) = \frac{\alpha^2}{2(1-\alpha)^2}[S^{[1]}(t) - 2S^{[2]}(t) + S^{[3]}(t)] \tag{2.18}$$

2.5.4 Winters method

When seasonal influence exists along with trend effect, Winters method is capable of accounting for these characteristics in the data. The model for predicting future demand at lead time T is given by [13]:

$$y(t+T) = (a(t) + b(t).T)F^* \tag{2.19}$$

where, F^* = best estimate for seasonal factor, F(t).

The estimates of the coefficients a(t) and b(t) and the updated seasonal factor F(t) are expressed as:

$$a(t) = \alpha(\frac{x(t)}{F(t-N')}) + (1-\alpha)(a(t-1) + b(t-1)) \tag{2.20}$$

$$b(t) = \beta(a(t) - a(t-1)) + (1-\beta)b(t-1) \tag{2.21}$$

$$F(t) = \gamma(x\frac{(t)}{a}(t)) + (1-\gamma)F(t-N') \tag{2.22}$$

where

N' = number of observations comprising seasonality.

α, β, γ = exponential smoothing coefficients $0 < \alpha, \beta, \gamma < 1$

2.5.5 General exponential smoothing (GES)

The general exponential smoothing model for the load at time t, y(t), is expressed linearly in terms of known (fitting) functions in the form:

$$y(t) = \beta(t)^T f(t) + \varepsilon(t) \tag{2.23A}$$

where,

f(t) = fitting function vector for the process

$\beta(t)$ = coefficients vector

$\varepsilon(t)$ = a white noise

T = transpose operator

The load model can be written in a vector form using the recent N sampled observations as:

$$Y = X^T\beta + \mathrm{E} \tag{2.23B}$$

where,

Y = process observation in N periods

= $[y(1),\ldots,y(N)]^T$

X = fitting function for the process

= $[f(-N+1),\ldots,f(0)]^T$

β = estimates of the coefficients with zero noise

= $[\beta_1, \beta_2, \ldots, \beta_M]^T$

$\mathbf{E}$ = load residuals (white noise) in N periods

The noise or load residuals has the following covariance matrix

$$V(\mathrm{E}) = \sigma^2\Omega^{-1} \tag{2.24}$$

where,

$$\Omega = \begin{bmatrix} w^{N-1} \ldots 0 \; 0 \\ \ldots \quad \ldots\ldots\ldots \\ 0 \quad \ldots w^1 \; 0 \\ 0 \quad \ldots 0 \; w^0 \end{bmatrix}$$

Usually the weights (w's) lie between 0.7 and 0.95 [49].

The estimates of the coefficients are found using weighted or discounted mean square error, i.e. minimizing

$$\sum_{j=0}^{N-1} w^j \,[y(N-j) - f^T(-j)\beta]^2 \qquad 0 < w < 1 \tag{2.25}$$

The minimization of the previous process yields the estimate vector of the coefficients as:

$$\hat{\beta}(N) = F^{-1}(N)h(N) \tag{2.26}$$

where,

$$F(N) = \sum_{j=0}^{N-1} w^j f(-j)f^T(-j) \tag{2.27}$$

$$h(N) = \sum_{j=0}^{N-1} w^j f(-j)y(N-j) \tag{2.28}$$

The forecast of the series at lead time ℓ is found [14,49] as:

$$\hat{y}(N+\ell) = f^T(\ell)\hat{\beta}(N) \tag{2.29}$$

The coefficients estimates and the forecasts can be updated respectively using:

$$\hat{\beta}(N+1) = L^T\hat{\beta}(N) + F^{-1}f(0)[y(N+1) - \hat{y}(T)] \tag{2.30}$$

$$\hat{y}(N+1+\ell) = f^T(\ell)\hat{\beta}(N+1) \tag{2.31}$$

where,

$$F = \lim_{N \to \infty} F(N)$$

This matrix is assumed to exist for all smoothing constants and fitting functions selected. The L matrix is usually constructed on the basis that the model will have a fitting function satisfying the relationship:

$$f(t) = Lf(t-1) \tag{2.32}$$

Application of the smoothing techniques for load forecast is not popular. Few proposed applications are found in the literature and are summarized here.

Christiaanse [50] proposed an exponential smoothing model for hourly load over a one-week period. This model consists of a constant part, C, and a Fourier series with "m" frequencies and a weekly periodicity w_i. This selected model has the form

$$y(t) = c + \sum_{i=1}^{m}(a_i \sin w_i t + b_i \cos w_i t). \tag{2.33}$$

where,

$$w_i = \frac{2\pi}{168} K_i \tag{2.34}$$

K_i = positive integer less than 84 (Nyquist limit) [50].

the forecast for lead time ℓ is found as

$$\hat{y}(t+\ell) = f(t+\ell)^T \hat{\beta}(t) \tag{2.35}$$

where,

$\hat{\beta}(t)$ = estimates of the coefficients of equation

f(t) = fitting function satisfying equation (2.32).

The estimates of the coefficients are expressed by equations (2.26) through (2.28) where the fitting function is expressed as:

$$f(t) = \begin{bmatrix} \sin w_i t \\ \cos w_i t \\ \cdot \\ \cdot \\ \cdot \\ \sin w_m t \\ \cos w_m t \end{bmatrix} \tag{2.36}$$

The update of the estimates and the forecasts are performed respectively using equation (2.30) and equation (2.31).

Christiaasne [50] proposed an extensive analysis to select the fitting functions and to find the proper smoothing constant. He extended this method by forecasting the error using an autoregressive model with lags of 1 hour and 24 hours. The forecast results for short lead times using the extended model were more accurate.

Phi et. al. [51] have used the Christiaanse proposed method to generate hourly forecasts up to 168-hour lead time. The forecast obtained was modified in order to account for the effect of weather temperature. Such modification was based on a one year data analysis to yield for each month the required megawatt adjustment per degree difference [11].

Settlage [52] proposed a two-stage statistical procedure to forecast short-term power system load. The first stage is to forecast the load shape or typical load in terms of its major components. The second stage is to forecast the residual of the load in terms of previous residuals.

The model of the load shape for day d and hour h is expressed as:

$$y_w(d,h) = x_0 + x_1.W + SL_w(d,h) \tag{2.37}$$

where,

$y_w(d,h)$ = typical load estimate for the given day-hour of week W.

x_0 = base load estimate of the given day-hour

x_1 = growth rate estimate of the given day-hour

W = week number

$SL_W(d,h)$ = seasonal weather load at the given day-hour of week W.

The seasonal weather component is expressed in terms of four harmonic components as

$$L_W(d,h) = \sum_{i=1}^{4}(X_{2i}\sin i\omega t + X_{2i+1}\cos i\omega t) \tag{2.38}$$

where,

$$\omega t = \frac{2\pi W}{52} \tag{2.39}$$

$X_2,\dots,X_9$ = seasonal function coefficients

The initial values of the coefficients were found using three years of historical data. These coefficients were updated using a forward and backward Kalman filters to delete the effect of the oldest observations and to account for the effect of the new observations.

The forecast of the residual was found for the next day-hour using double exponential smoothing statistics as:

$$R(d,h) = \sum_{i=0}^{4} \alpha(1-\alpha)^i S(d,h-i) + (1-\alpha)^5 S(d,h-23) \tag{2.40}$$

where,

α = a smoothing constant

$S(d,h\text{-}i)$ = single exponential component statistics for the i^{th} hour prior to the day-hour considered.

The single exponential statistics are expressed in terms of the residual forecasts as:

$$S(d,h) = \sum_{i=0}^{4} \alpha(a-\alpha)^i r(d,h-i) + (a-\alpha)^5 S(d,h-23) \tag{2.41}$$

where

$r(d,h\text{-}i)$ = the difference between the actual and typical load for the i^{th} hour prior to the day-hour considered.

Sachdev et. al. [53] proposed an exponential smoothing model for on-line application. This model consists of two components [11]. The load component for day (d) and hour (h) is assumed as

$$y(d,h) = y(d-1,h) + (1-\alpha_d)[\hat{y}(d-1,h) - y(d-1,h)];\ 0 \le \alpha_d \le 1 \tag{2.42}$$

The error component is expressed using a model similar to the load component as given by equation (2.42).

Feuer [54] introduces a technique for forecasting with adaptive gradient exponential smoothing (AGES). This technique is based on exponential smoothing methods. The technique has been applied on simulated data. The results showed that this technique has a strong convergence property.

It appears from the preceding discussion that the smoothing constant or constants will be a major factor in determining an accurate forecast. Since the smoothing constant is found by trial and error and may not be revised as the process changes with time, this dependency creates a drawback in these techniques. This method has usually been used for short-term load forecasting.

2.6 State Space and Kalman Filter

In this method, the load is modeled as a state variable using state space formulation. The model assumed could include other states, if they are needed for modeling the process such as load growth and load seasonalities. Other effects on the load, such as that of weather conditions, can be accounted for by using this approach.

The state space model is written in the form [55].

$$X(k+1) = \Phi(k)X(k) + W(k) \tag{2.43}$$

$$Y(k) = H(k)X(k) + V(k) \tag{2.44}$$

where,

X(k) = (n x 1) process state vector at time t_k

$\Phi(k)$ = (n x n) state transition matrix relating X(k) to X(k + 1) when no forcing function exists.

W(k) = (n x 1) a white noise with a known covariance Q(k)

Y(k) = (m x 1) vector measurements at time t_k

H(k) = (m x n) matrix relating X(k) to Y(k) without noise

V(k) = (m x 1) measurement error which is a white noise with known covariance R(k)

The covariance matrices for the vectors W(k) and V(k) are given by:

$$E(W(k), W(i)^T) = \begin{bmatrix} Q(k) & i = k \\ 0 & i \neq k \end{bmatrix} \tag{2.45}$$

$$E(V(k), V(i)^T) = \begin{bmatrix} R(k) & i = k \\ 0 & i \neq k \end{bmatrix} \tag{2.46}$$

and

$$E(W(k), V(i)^T) = 0 \textit{ for all } k \textit{ and } i \tag{2.47}$$

At any instant t_k there will be an estimate for the process based on knowledge of the process up to t_{k-1}. This estimate is called the priori estimate and is expressed as X (k/k-1). The associated error between the actual and the previous estimate of the process is given as.

$$e(k/(k-1)) = X(k) - X(k/(k-1)) \tag{2.48}$$

This error vector has an error covariance matrix expressed by

$$E(e(k/(k-1)), e(k/(k-1))^T) = P(k/(k-1)) \tag{2.49}$$

The updated (a posteriori) estimate is obtained as a linear combination from the a priori estimate and the measurement noise as:

$$x(k/k) = X(k/(k-1)) + K(k)x[Y(k) - H(k)X(k/(k-1))] \tag{2.50}$$

where

X(k/k) = updated estimate

K(k) = blending factor

The error associated with the actual and the updated estimate of the process is

$$e(k/k) = X(k) - X(k/k) \tag{2.51}$$

The covariance matrix of this error vector is expressed by

$$E(e(k/k), e(k/k)^T) = P(k/k) \tag{2.52}$$

The blending factor K(k) is found such that X(k/k) is optimal in some sense such as the minimum mean-square error (MSE) criterion. This factor is known as Kalman gain and the procedure for implementing Kalman filter for load prediction is as follows [55].

1. Find the process periori estimate X(k/k-1) and the error covariance matrix associated with it P(k/k-1).

2. Compute the Kalman gain

$$K(k) = P(k/k-1)H(k)^T(H(k)P(k/k-1)H(k)^T - R(k)^{-1}) \tag{2.53}$$

3. Compute the updated estimate error covariance matrix.

$$P(k/k) = (1 - K(k)H(k))P(k/k-1) \tag{2.54}$$

4. Project ahead a priori estimate X((k+1)/k) and the error covariance matrix P(k+1/k) associated with it.

$$X(k+1/k) = \Phi(k)X(k/k) \tag{2.55}$$

$$P(k+1/k) = \Phi(k)P(k/k)Q(k)^T + Q(k) \tag{2.56}$$

5. Go to Step 2 moving to the next time step.

It is clear that the state space method is very attractive for on-line prediction as a result of the recursiveness property of Kalman filter. The optimal forecast which is generated will be based on the assumed model. Therefore, the model has to be known prior to using Kalman filter. The identification process is the main difficulty of this approach. Mainly the noise covariance matrices Q(k) and R(k) are not easily estimated.

Kalman and Bucy [56,57] proposed this technique of state estimation and sequential filtering known as Kalman filter in 1960. The application of this technique for load forecasting came almost a decade later by Toyoda et. al. [58,59] who applied it to the short-term load forecast. Toyoda et. al. [58] suggested three models for different lead time predictions as follows:

i) For a very short time (5 to 10 minutes) where no large fluctuation exists with the load, the model is expressed as

$$x(k+1) = x(k) + w(k) \tag{2.57}$$

$$y(k) = x(k) + v(k) \tag{2.58}$$

ii) For a short-term prediction from 10 minutes to one hour where fluctuation has to account for, the model is expressed as

$$\begin{bmatrix} x(k+1) \\ \Delta(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x(k) \\ \Delta(k) \end{bmatrix} + \begin{bmatrix} w_1(k) \\ w_2(k) \end{bmatrix} \tag{2.59}$$

$$y(k) = [1 \quad 0] \begin{bmatrix} x(k) \\ 0(k) \end{bmatrix} + v(k) \tag{2.60}$$

iii) For hourly or daily forecast where periodical and load pattern have to be accounted for, the model is expressed as

$$\begin{bmatrix} x(k+1) \\ \Delta(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \alpha(k) \end{bmatrix} \begin{bmatrix} x(k) \\ \Delta(k) \end{bmatrix}$$

$$+ \begin{bmatrix} 0 & 0 \\ \beta(k) & \sigma(k) \end{bmatrix} \begin{bmatrix} T(k) \\ H(k) \end{bmatrix} + \begin{bmatrix} w_1(k) \\ w_2(k) \end{bmatrix} \tag{2.61}$$

$$y(k) = [S(k) \quad 1] \begin{bmatrix} x(k) \\ \Delta(k) \end{bmatrix} + v(k) \tag{2.62}$$

where,

x(k)	=	system load
y(k)	=	observation value of load
w(k)	=	system noise
v(k)	=	observation noise
Δ(k)	=	load increment
T(k)	=	temperature
H(k)	=	humidity
S(k)	=	daily standard load pattern coefficient
α(k),β(k),σ(k)	=	coefficients

All coefficients are estimated from historical observations.

Toyoda and Chen [60] suggested 10-minute, hourly and daily models similar to those of Toyoda et. al. [58,59]. The estimation technique of [58,59] is used along with examining the correlation between the load forecast errors and the weather variables for accuracy improvement.

Gupta and Yamada [61] suggested two complex models for load forecasting. The first model is for 1 to 24 hour forecast and the other model is for daily peak forecast. The 1 to 24-hour model expressed at hour j and day i is written as:

$$y(i,j) = B(i,j) + WC(i,j) + x(i,j) \tag{2.63}$$

where,

$y(i,j)$	=	Hourly measured MWH load
$B(i,j)$	=	Basic load component
$WC(i,j)$	=	Weekly cycle component
$X(i,j)$	=	Residual component containing the weather variation effect

The peak load model for the i^{th} day is given by

$$y_p(i) = B_p(i) + S(i) + WS(i) + \varepsilon(i) \tag{2.64}$$

where,

$y_p(i)$	=	peak load
$B_p(i)$	=	basic load component
$S(i)$	=	weekly pattern component
$WS(i)$	=	weather sensitive component
$\varepsilon(i)$	=	a random component

The weekly pattern component, S(i), takes the value of weekly pattern corresponding to the day modeled. The weather sensitive component, SW(i), is expressed as a linear combination of transformed weather variables as those given by equation (2.5).

Girgis et. al. [62] proposed a recursive optimal estimator for power system modeling and forecasting. They use a similar technique as that of Szelag [63] which has been proposed for short-term forecasting of trunk demand. The model proposed by Girgis et. al. [62] for the hourly load, y(t), is represented by two components. The first component,$y_1(t)$ is a constant part component and is expressed as:

$$y_1(t) = f_1(t) \tag{2.65}$$

where,

$f_1(t)$ = a white noise.

The second component, $y_2(t)$ is an oscillatory part component and is expressed as:

$$y''_2(t) + \omega^2 y_2(t) = f_2(t) \tag{2.66}$$

where,

$f_2(t)$ = a white noise independent of $f_1(t)$.

ω^2 = oscillation frequency

The state variables are chosen as y_1, y_2, y'_2 respectively. The Kalman filter previously discussed is implemented for the prediction process assuming different covariance values for the white noise.

There are other approaches and methodologies which utilizes the Kalman filter theory. These include the work of Sharma et. al. [64], Singh et. al. [65], Galiana et. al. [66,67], Panuska et. al. [68,69], and Campo et. al. [70].

Some of these researchers have adapted other modeling techniques so that the Kalman filter theory could be used. For example Sharma et. al. [64] have used a model proposed by Christianse [50] based on general exponential smoothing and a Kalman filter. Singh et. al. [65] have used an autoregressive AR model of order p. Recently Campo and Ruiz [70] have used Box and Jenkins time series modeling methodology [22] along with Kalman filter to get an adaptive weather sensitive short-term forecast.

A close look at these papers, the state space modeling and the Kalman filter theory in particular, shows the suitability of this technique for on-line calculation. Many modeling approaches are modified to work with Kalman filter thus allowing them to be adaptive and capable of updating the model parameters as new observations (i.e., load measurements) become available. This method has usually been applied to the short-term load forecasting.

2.7 Other Conventional Methods

There are other modeling techniques that have been used in load forecasting. These techniques include spectral decomposition, pattern recognition, Bayesian modeling, multivariable load modeling and other modeling techniques that have been implemented for certain applications. A review of some such papers is presented next.

Dehdashti et. al. [71] have developed an algorithm based on pattern recognition techniques to forecast hourly load demand up to 24-hour lead time with the use of forecasted weather variables. The algorithm was proposed for forecasting load demand in small area power systems where uniform weather patterns exist.

Srinivasan et. al. [72] have developed a method for forecasting hourly load demand using multiple correlation models. In this method, different prediction models corresponding to the hourly, daily, weekly, and yearly correlation periods are assumed. The forecast is obtained using the prediction values of these models together in an optimal combination. Forecasts for holidays are improved if some of these predicted component values are rejected. The temperature effect is not included in such modeling.

Bunn [73] has investigated the method of Bayesian model discrimination for forecasting daily electricity load demand. This method is explained as being an extension of the standard load construction method. The load forecasts are obtained by knowing the differing demand models and the probabilities associated with them. Continuous updating of these probabilities are to be made as new data become available.

Singh et. al. [74] have proposed a multivariable load forecasting approach real time monitoring of power systems. This has been achieved using a multivariable state space model for the load of multinodes. The model parameter estimates are found using both the extended Kalman filter and another adaptive estimation techniques developed by Kashyap [75]. This approach requires a huge computational effort [11].

Van Meeteren et. al. [47] have proposed a short-term load forecast algorithm using a combination of different models. These models include a nominal load, a weather sensitive load, and a residual load. Each of these models is predicted separately by using a special approach for the identification and estimation of the parameters. The algorithm proposed is able to work for on-line applications.

Other approaches that have been applied for certain applications include the work of McRae et. al. [76], Ross et. al. [77], Willis et. al. [78], Broehl [79], Letter et. al. [80], Krogh et. al. [81], and Michaelson et. al. [82].

The diversity among the methods used in load forecasting indicates the problem of load forecast is not bounded. It can be addressed from different perspectives. However the final goal is to get a forecast which is accurate, adaptive, robust, and economic.

2.8 Rule-Based Approach

Rahman and Bhatnagar [2,4] were the first to investigate the applicability of expert systems (rule-based) to short-term load forecasting. They have developed two similar algorithms. One produces one-to-six hour ahead forecasts and the other produces one-to-twenty-four hour ahead forecasts. The absolute average error in the forecasts range from 0.869% to 1.218% in the six-hour forecast algorithm and 2.429% to 3.3% in the 24-hour forecast algorithm.

Rahman and Baba [83,84] have extended the work to 24-hour load forecasting while integrating demand-side control. This algorithm is claimed to have the following features [83]:

- The algorithm requires an on-line database of only one to two weeks of load and weather data.

- The algorithm does not require a large number of computations.

- The algorithm has a built-in revising mechanism able to modify the preselected rules if the average error of previous three days forecast continues to be more than a certain pre-determined limit.

- The algorithm uses Extended Fortran Language (EFL), Ratfor Language, and C language together for defining the rules of the rule-base in an easy and efficient manner.

- The algorithm has the ability to work continuously and has the ability to transfer information to other systems.

Jobbour et. al. [3] designed an expert system called ALFA (Automated Load Forecasting Assistant) to generate load forecasts up to 48-hour lead time. ALFA has a database of 10 years of load and 12 weather variables. The weather variables needed are obtained from the National Weather Service via a satellite interface. A rule-base has been used to generate the forecasts that is able to account for load growth and seasonalities (daily, weekly) besides special events and holidays.

Thus one can see that the application of a rule-base (or an expert system) has been limited to the short-term load forecast. Specifically, it has only been applied to the 1 to 24-hour forecast in the work of Rahman et. al. [2,4,83,84] and to the 1 to 48-hour forecast in the work of Jabbour et. al. [3]. A remarkable difference exists between these two work in terms of the size of the database requirement (few weeks compared to 10 years). This makes Rahman et. al. approach suitable for work on microcomputers.

2.9 Summary

An exhaustive survey of the load-forecasting algorithms has been conducted. A review of the different techniques that have been applied to the load forecasting problem has been addressed in this chapter. Each of these methodologies has been covered in terms of its modeling techniques followed by the applications that have been performed using such a methodology.

2.9.1 Model Variable Identification and Estimation

Identification of the appropriate model in any methodology is the cornerstone of such an approach. Therefore, sufficient data may be needed which could extend to several years in order to adequately identify the load model variables (or parameters) that best model the load as represented by the given data base. Although experience of the forecaster plays a major part in a successful and appropriate load forecast model, different methodologies apply different identification methods and possibly different estimation techniques. A summary of data base requirements, model identification and estimation, and adaptiveness and recursiveness is presented in Table 1.

MLR - Multiple Linear Regression

STS - Stochastic Time Series

GES - General Exponential Smoothing

SSKF - State Space & Kalman Filter

RBS - Rule-Based Systems

2.9.2 Error Analysis and Accuracy of Result

It is difficult to compare the five given methodologies as some are not appropriate for a given load data, and some may be more suitable for specific applications than others. These methodologies have been applied for different lead times using different data bases with various data depths. In addition to this, the forecaster's experience plays a major part in identifying the adequate load model in each methodology. As a result of these conflicts, the

Table 1. Summary of Various Characteristics of Five Load Forecasting Techniques

Charactrestic	Technique				
	MLR	STS	GES	SSKF	RBS
Analysis Data Base	16 Years	1 Year	2 Years	1 Year	1 Year
Forecast Data Base	3 Days	9 Days	None	None	1 Week (Selected Data)
Identification Method(s)	Correlation & Regression Analyses	Data Plots, ACF, PCF, and CCF (for TF Models)	Data Plots ACF, and Power Spectrum	Spectral Analysis	Operator Experience
Estimation Method(s)	Least-Squares	Maximum Likelihood	Discounted Least-Squares	Least-Squares	Statistics-Based Heuristics
Is the Method Adaptive?	No	No	Yes	Yes	Yes
Is the Method Recursive?	No	Yes	Yes	Yes	Yes

summary of the performances of the five major methodologies is presented in Table 2 with certain qualifications. The reader should bear in mind that the five techniques have been independently applied to five different data bases by five different researchers. Such results could give, though not precisely, an idea of the order of the error of each methodology subject to the caveats discussed above.

Table 2. Summary of Error Analysis for Five Load Forecasting Techniques

Technique	Qualification	Forecast Lead Time Interval		
		1-Hour	6-Hour	24-Hour
MLR	Average and Maximum Daily Peak Forecast (16 Summer Peaks)	N/A	N/A	5.7%(Max.) 2.4%(Ave.)
STS	Average Forecast Error of All Seasons (3 Weeks in each)	N/A	N/A	4.2% (ARIMA) 4.0% (TF) 3.97% (NLETF)
GES	Standard Error of 2 Years of Simulated Results	3.3% (Original Model) 2.0% (Extended Model)	N/A	4.5% (Original Model) 4.0% (Extended Model)
SSKF	Sum Squares of Forecast Errors (SSE) (24-Hour Load Cycle 1-Hour Forecast)	0.225 (Q-Matrix = 0) 0.0365 (Q-Matrix $\neq$ 0)	N/A	N/A
RBS	Average Forecast Error of All Hours of All Seasons	1.001%	3.113%	2.736%

Chapter III

NEED FOR ADAPTIVE FORECASTING TECHNIQUES

3.1 Introduction

Load forecast plays an important and an integral role in the various operations of electric utilities. For short-time periods (few minutes to hours and upto one week), the interrelationship between the load forecast and these operations can be demonstrated as shown in Figure 1 [85]. In this demonstration, load forecast is shown as the dynamo for the different power system operations. Consequently, load forecasts for different lead times are needed for the performance of these operations. As indicated earlier, it is proposed to develop load forecasting algorithms capable of issuing load forecasts for different lead times. Such algorithms would enable the design of integrated load forecasting schemes for different operational aspect of electric utilities as demonstrated in Figure 1. These forecasting schemes have to be sensitive (adaptive) to the variability in these operations as a result of the changes in the conditions affecting the performance of these operations. In other words, these forecasting schemes have to be able to react to the control actions taken by the operator. Such control actions could be issued based on predicted load demand in order to achieve some prespecified objectives. For example, based on load forecast issued, the peak load is expected to exceed a prespecified maximum value. Therefore, the operator will decide to issue some control actions to avoid such peaks. As a result of these actions, load will change not only when the control actions take place, but at later times as a payback for these control actions. Another example, based on the load forecast issued, the operator may find it economical to work on improving the load factor of the system. This can be done by using batteries and/or pumped storage so that this stored energy can be used to replace some of the peaking units such as gas turbines. Definitely as a result of these control actions the anticipated load will change and consequently the load forecast has to be revised to account for these changes.

Any load forecasting method is based on the assumption that the current and future values of the load will follow the same model as that of past load values. In other words, the future values of the load will be predicted based on the parameters estimated from historical observations. This assumption can only be true if future conditions affecting the future load are the same as those affecting its past values. Unfortunately, load shape behavior always varies and the parameters estimated from past information may not match those parameters under future circumstances affecting the load. In many cases, these variations could be tolerated. However, some other variations could cause abnormal changes in load behavior such as a large increase or decrease in load as a result of severe weather changes or any other influencing variable. These abrupt changes may not be correctly accounted for due to the attributed weight of the effect of the previous data observations that have been used for estimating the load-forecast model parameters. Therefore, in developing a forecasting algorithm, the developer has to bear in mind that the future conditions can not always be a replica of the past conditions in the sense discussed.

One other dimension that can be added to the complexity of load forecasting is projected by Rahman [85]. This complexity is represented by what is called "the scenario of spot pricing or service reliability driven pricing". This "scenario" means that the production cost of electricity can change intermittently as a result of meteorological conditions change. This

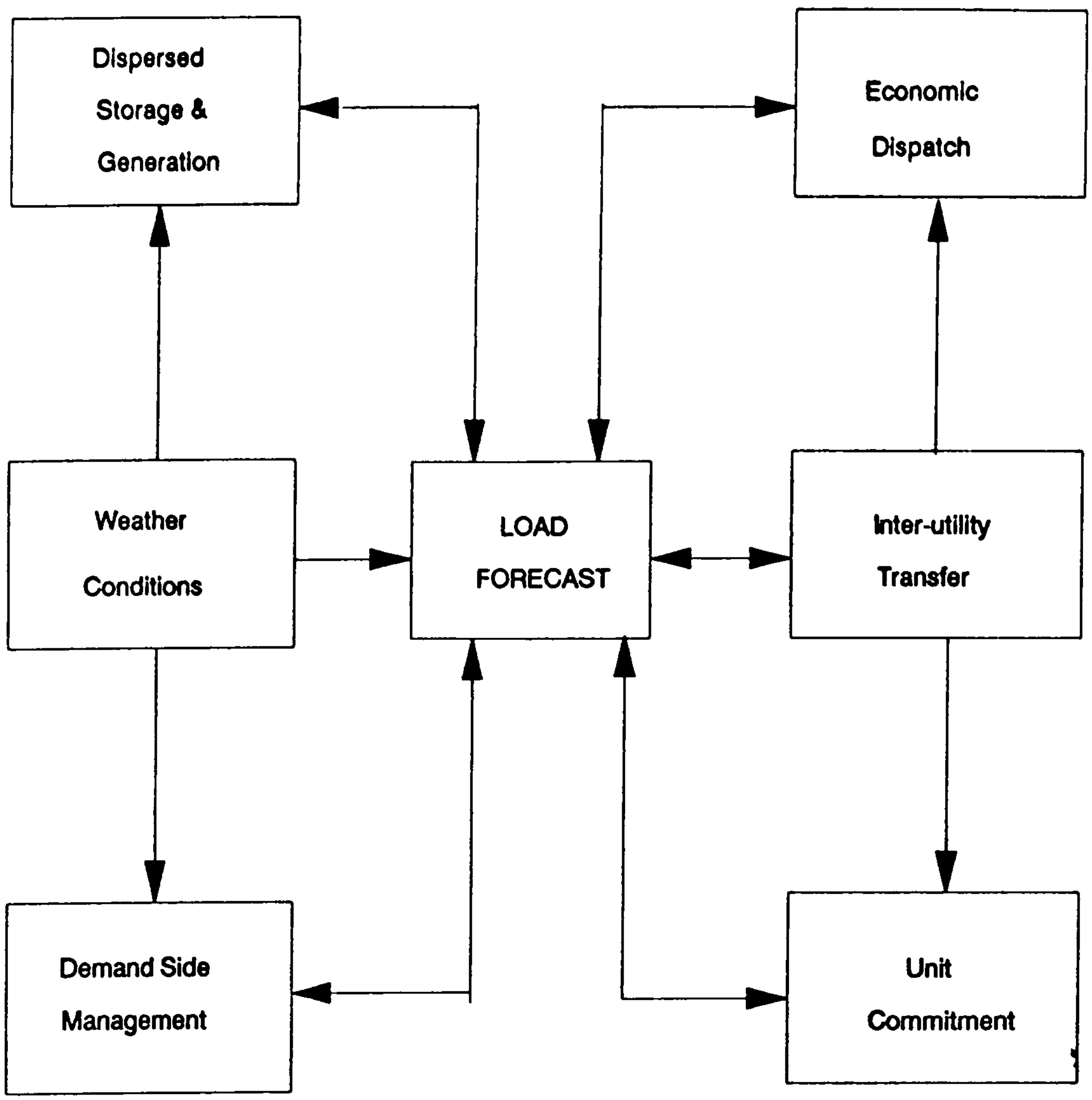


Figure 1. Load Forecast as an Integral Part of Utility Operations. (Source: Ref. 85)

dependency can be explained if intermittent generation sources such as wind mill generators and photovoltaic power generation panels comprise a significant part of the system energy generation resources. Therefore, this "scenario" will result in an impact on the load behavior. That is, the load will change its behavior according to the pricing system.

The next section, Section 3.2, discusses the role of load forecasting in the operation of electric power industry. A coverage of the required features in any load load forecasting algorithm is next conducted in Section 3.3. Each of these features is covered in a subsection by an explanation signifying its importance. A detailed presentation has been given to the feature of adaptiveness to stress its significance in the design of load forecasting systems. The planned objectives are covered next in Section 3.4. The direction of the research is planned towards investigating the conventional load forecasting methods along with the expert system approach to load forecasting. This is followed by discussion of the appropriateness of the knowledge based approaches to the problem of load demand forecasting, especially to the 168-hour load forecast as covered in Section 3.5. In Section 3.6, benefits from the combination of the statistical and the knowledge based approaches to the load forecasting problem is presented. Finally, a summery for this chapter is covered at section 3.7.

3.2 Role of Load Forecast

The role of load forecasting is very important in many operations of the electric power system. As mentioned earlier, these operations include unit commitment, energy transfer scheduling and load dispatch, coordination of energy management programs with the system resources, maintenance service and fuel supply scheduling, and others.

Unit commitment is the process of scheduling the system generating plants by advance planning for the start-up and the shut-down of these generating units. This process is performed to meet the load demand with the required reserve margin at the minimum operating cost taking into account the required degree of system security. The role of load forecasting here (short-term) is that the load demand has to be predicted to carry out this process. A successful and economic unit commitment operation will rely on how accurate is the predicted load or the forecast.

Energy transfer scheduling and load dispatch is the process of minute-to-minute economic allocation of the output of the generating units. Such process is performed in order to meet the load demand at the minimum operating cost taking into account the tie-line scheduled energy. The role of load forecasting here (short-term) is that the prediction of the load demand with good accuracy is important for two purposes. First, the decision for selling or buying energy will be carried out according to these forecasts. Second, the economic operations (scheduling and dispatching) of the generating units will rely on these forecasts and their accuracy.

Coordination of the energy management programs with the system resources is the process of altering the load curve such that the peak load demand is reduced or shifted to other times where the available resources are capable of supplying this demand economically. This includes the case when electricity is bought from neighboring utilities. The role of load forecasting here (short to medium-term) is predict the peak demand accurately. Besides predicting the peak demand and its time of occurrence, prediction of the peak demands of the neighboring utilities and the time for their occurrence are also required when electricity is bought from these utilities. It is also of importance to know whether these neighboring systems will use any energy management programs or not. If so, how these programs will affect the effectiveness of these systems' own energy management programs and what remedies should be applied.

Maintenance scheduling is a necessary process for any operating system. This process needs to be planned in advance so that economic consideration could be justified for this process. Usually, maintenance is performed for each unit during the time periods when there is no need for its generating capacity. This becomes more critical if the unit scheduled for maintenance comprises a significant percent of the system capacity and if the unit is considered as a "base" generating unit. Usually, an optimum maintenance scheduling is planned based on the generating unit's characteristics and the forecasted load demand. Therefore, scheduling of the generating units for maintenance service requires an accurate short to medium-term load forecast to achieve this process in a successful and economic manner.

Fuel scheduling is based on contracts which could vary in nature and/or duration. The concern here is how such scheduling will insure sufficient fuel for the required generation plus the required fuel reserve through a prespecified planned period. A good prediction of the energy consumption can justify the required fuel scheduling as planned by these contracts. Such prediction of the energy consumption can be estimated from the load forecast of the intended fuel scheduling period. Therefore, an accurate load forecast will result in better planning for fuel supply scheduling.

3.3 Features Required in Load Forecasting Algorithm

There are many features that are required when designing a short-term load forecasting algorithm. These features are pointed out as follows.

3.3.1 Adaptivity

The load forecast model can not be considered or assumed stationary (or fixed) indefinitely. This variability can be viewed in two aspects. The first aspect is the variability in the load forecast model due to the changes of external influencing variables. This includes the the effect of changes in seasonal and meteorological variables. The second aspect is the variability in the load forecast model due to the changes in internal (to the system) influencing variables. This include the effect of control actions such as those resulted from the application of energy management programs. Therefore, the design of realistic load forecasting system requires that the load forecast model be adaptive as regarding both the changes in its parameters and as regarding the changes in its structure.

3.3.1.1 Parameter adaptivity

Load-forecast model parameters may change with time due to seasonal and meteorological variables changes. Therefore, the load forecast model has to adapt to the changes of its parameters. This is very important if good and accurate forecast is required.

Adaptiveness due to the changes in the model parameters can be viewed in two senses. The first sense is updating of the parameter estimates as new observations become available to account for the new conditions associated with the new measurements. For example, recursive algorithm such as Kalman filtering could update the parameter estimates as every new observation becomes available to the algorithm. Alternatively, re-estimation of the model parameters can be performed using the new available measurements if the need arises. The second sense is updating the model parameters themselves in order to account for the seasonal changes. For example, in the winter wind chill is an important parameter in the short-term forecasting; while in the summer, it is not of such importance. On the other hand, relative humidity is an important parameter in the summer but it has little importance in the winter. Therefore, each season should have its own algorithm adapting the parameters which play an important role in the process of load forecasting during that season.

3.3.1.2 Structure adaptivity

Load-forecast model structure may change as a result of the control actions that could be taken by the system operator for energy management purposes. Therefore, these changes in the load process (or its structure) has to be adapted to the control actions if good and accurate forecast is required.

Adaptiveness due to the changes in the load process (or structure) can also be viewed in two senses. The first sense is updating the load predictions to reflect the effect of control actions as given by the energy energy management programs. For example, if the generation is to be reduced by certain MW at the time of expected peak, then such reduction should be reflected in the predicted values of the load in the hour of the peak and subsequent hours as a result of the payback of this control action. The second sense is rebuilding of the load process as new observations become available by removing the effect of the control action and its subsequent results. this process is very important to make it the load process as natural as possible in order to allow its modeling in stochastic sense. For examples, the action of peak reduction mentioned by certain MW has to be reversed ~~to~~ restructured to rebuild the load curve as if there were no control action issued. or

3.3.2 Recursiveness

This means that as new data become available they are used in updating the data base needed to generate the new forecasts. This has to be done without any necessity for updating the model parameters for each forecast. For example, in each season the next load forecast will be calculated using the same model utilizing the actual data as they become available. Such calculation will be based on an assumption that the algorithm is capable to span the whole season with the same model parameters.

3.3.3 Computational economy

Load forecast algorithms need to be executed economically as regarding both of the core storage and the execution time. The core storage can be minimized by reducing the data needed to generate the load forecast. The execution time can be minimized by a using computers with sufficient speed. This issue becomes more clear with the application of expert system methods to the problem of load forecasting where both of these requirements are satisfied.

3.3.4 Robustness

A robust load forecasting algorithm would have the following characteristics:

1. There may be circumstances where the situation on hand does not match with the rule base. In such cases the algorithm should still be able to generate reasonable forecast values.

2. There may be measurement errors resulting in some bad load or weather data. Such bad data have to be detected by the algorithm and discarded prior to generating the forecast. Usually this is done by implementing a filtering routine in the algorithm which is capable of detecting these bad data.

3. There may be circumstances where the new load and/or weather data needed to update the data base are not available. This can happen if the communication network which transmit them is faulty for example. Then, there should be some default data values which still can generate a suitable forecast.

3.4 Planned Objectives

The proposed objectives of this research include developing forecasting schemes for short-term (both hourly and daily peak) load demand prediction upto one-week lead time. These forecasting schemes are essential for the design of a complete operating system. Such developed schemes have to implement all the desired features required in load forecasting algorithms. This means these algorithms have to be adaptive in accounting for the load parameter changes, recursive to account for the information obtained in the new load observation available, robust in issuing forecasts with good accuracy, and computationally economic as regarding the execution time and the data base requirement.

The research will investigate the conventional forecasting methods as well as the expert system approach to load demand forecasting. The conventional method will be investigated in order to develop forecasting algorithms that are capable of implementing the previous mentioned features required in load forecasting algorithms. These algorithms may be developed using a combination of different conventional methods that could result in better forecasts. The investigation of the conventional methods will such that these algorithms work under a complete load forecasting system that work under a knowledge-base approach. The range of this conventional techniques will investigated to higher lead time, namely upto one week lead time. The reason behind this constraint is that this range has not been extensively investigated by the conventional methods. The expert system approach will be investigated on its applicability to tackle the short-term (1 to 168 hours) and daily peak (one to seven days) load forecast. Both of these ranges have not been investigated yet by the expert system approach. Some combination of conventional methods and the expert systems approach could be used if this results in a robust and accurate forecasts. An investigation for this possibility will be conducted following the separate development of the algorithms by both approaches.

3.5 Appropriateness of Rule-Based Approach.

The 168-hour load forecast is quite appropriate for implementation using a rule-based approach if sufficient rules about this process could be extracted so that reasonable forecasts can be generated. More rules could be extracted as experience is increased or obtained from experts in this field. The appropriateness of the rule-based algorithm to the 168-hour load forecast can be justified as follows:

- The nature of the 168-hour load forecast (and higher lead time forecasts in general) is suitable for rule-based techniques. Such suitability is based first on the fact that qualitative forecasts get more accurate as the forecast lead time increases. Second, it is based on the fact that operator experience plays an important role in judging whether the results obtained using algorithmic (statistical) methods are acceptable based on his experience. Third, in many instances forecasts issued based solely on the operator experience is an acceptable practice for many utilities. Such predictions could be produced when the algorithmic (statistical) methods are likely to fail to predict appropriate load forecasts as a result of the lack of adaptiveness of these algorithms to varying future conditions.

- The complexity of the 168-hour load forecast (and load forecast in general) dictates that rule-based approach could be appropriate to such a complex problem. This complexity rises from the fact that many factors are involved in the demand for electricity. These factors have different effects at different times and at different magnitudes. Algorithmic (statistical) methods are unable to account for all influencing factors as a result of the following:

  - Assuming all (external) factors or variables affecting the load are continuously significant and a multiple input-single (or multiple) output linear modeling approach (statistical) can be used. Then such a load forecast process requires huge computational resources. This modeling approach is of high cost. On the other hand, many influencing factors are of intermittent effect and some others have a nonlinear effect. Therefore, some factors could be dropped as they show no significant correlation with the load, while other factors will be modeled linearly where, in fact, they have a nonlinear effect. The rule-based approach is promising in dealing with the effect of these many variables if rules and functions could be devised to account for their effect. On the other hand, burden of computation for the search for a "practical" load forecast could justify the cost of building an knowledge-based expert system in the long run.

- There are other factors or variables (internal) affecting the load which are imposed by the system operator as a result of the operations of the energy management systems. These factors affect the predicted load as well as altering the natural load demand measurement. A knowledge-base system can handle this complexity. First, all the control actions performed by the operator could be stored in the system data base. Then through the rules developed from the system experts and the given functions of the impact of such control actions, the knowledge-based expert system can issue modified forecasts that have accounted for the effect of the control actions. As measurements become available, the knowledge-base system will be able to readjust the load measurements by removing the effect of the imposed control actions. Such removal of the effect of the control actions will be performed to make the load demand process as close as possible to its natural behavior. Such natural behavior is more likely to produce more accurate forecasts than those forecasts which are produced using the altered (or the disturbed) load behavior by the control actions.

- There is another complexity that can be added to the load forecast problem. This complexity is projected by Rahman [85] and is represented by what is called "the scenario of spot pricing or service reliability driven pricing". This "scenario" means that the production cost of electricity can change intermittently as a result of meteorological condition changes. This dependency can be explained if intermittent generation sources such as wind mill generators and photovoltaic power generation panels comprise a significant part of the system energy generation resources. Therefore, this "scenario" will result in an impact on the load behavior. That is, the load will change its behavior according to the pricing system. Definitely the statistical techniques by themselves will fail to handle all information involved with this complexity. The use of a knowledge-based load forecast expert system should be able to handle this problem through finding and building rules and functions that can handle the various aspects of this "scenario".

- The scope of the load forecast problem is too broad, since it touches most if not every aspect of the operation and planning of electric utilities. A comprehensive knowledge-based system requires several man-years of group work. Therefore, the scope has been defined from the problem at hand as the 168-hour load forecast. This scope has been chosen because of the following facts:

  1) No rule-based approach has been applied to higher lead time than 48-hour. Namely, the work of Rahman and Bhatnagar [2], and Rahman and Baba [83] have addressed the load forecast upto 24-hour lead time and the work of Jobbour et. al. [3] has addressed the load forecast upto 48-hour lead time.

  2) No rule-based approach in an artificial intelligence environment has been developed for higher lead time than 24-hour using a personal computer. The work of Rahman and Bhatnagar [2] and Rahamn and Baba [83] have been applied using personal computers. These programs have been developed using FORTRAN language to forecasting load upto 24-hour lead time. The work of Jobbour et. al. [3] has been applied using a IBM-3090 mainframe computer. This program has been developed using LISP language and uses a large data base extending upto 10 years of hourly data of eleven variables.

  3) The developed rule-based algorithm will be suitable for microcomputer applications.

3.6 Benefits from Combined Rule-Based and Statistical Approaches

It would be very beneficial to have a combinations of rule-based and statistical load forecasting technique upto 7-day lead time. The reason behind this affirmative answer can be explained by the following:

1. The expertise in the load forecast domain that is needed for building the knowledge-based expert system can not be claimed to exist such that it spans every condition or circumstance that could be faced in the load forecast process. Building a

knowledge-based expert system is a dynamic process. This means that expertise can be increased as knowledge about the system is expanded. This expanded knowledge is transformed through the experience of experts into more rules in the knowledge-base to cover new circumstances. Therefore, there will exist especially in the early stages of the rule-base algorithm performance,a need for the statistical algorithms to cover these gaps where the system is "unable" to deduce "accurate" load forecasts using the given rules in the knowledge-base of the expert system.

2. The statistical methods are not a pure science in the sense that the forecaster experience plays a major part in developing a load-forecast model for the load forecast process, which makes forecasting processes to be described, as an art. This experience includes manipulating the data, transforming it, searching for the appropriate explanatory variables, and finding the appropriate load forecast model that can produce forecasts with the most likely accuracy for the a given application under a given circumstance. In this case, the knowledge-based expert system can be built so that forecasts can be produced: (i) Using the rules and functions that have been extracted from expert(s) and have been developed into the knowledge-base of the expert system. (ii) Using statistical modeling methods that are controlled by the the knowledge-based load forecast expert system. The statistical method forecasts could be produced from different load forecast models possibly using different statistical modeling techniques that are controlled by rules built in the knowledge-base of the load forecast expert system. These forecasts could be displayed to the system operator along with the forecast confidence intervals or certainty factors for the required lead time. The operator can ask the knowledge-based system for interpretation of the results and on explanation of how these results were obtained so that he can select the best forecast for the conditions at hand. This could be very beneficial in real time where the load-forecast expert system is a part energy management systems.

3. The rule-based approach could be used with statistical methods such that it can rectify the forecasts produced by statistical methods where these method are unable to adapt

for varying conditions. Also the rule-base approach could be used to modify the data that will be used with statistical methods such as removing the effect of variables which could not be accounted for using these statistical techniques.

4. Another deeper applicability of both the rule-base approach and statistical methods is the design of a knowledge-based system which acts as a load forecaster. This means this system can analysis the data, select the variables that can explain this data, and select a method or methods which can produce a good forecast for this load process. This could be beneficial in cases where the load model needed to be reexamined frequently. This need for reexamination of the load forecast model comes as a result of the variability of the factors that are used in building the load forecast model and also as a result of the variability in the estimates of load forecast model parameters.

3.7 Summary

The proposed research objectives have been discussed in this chapter. Knowledge of the role of the load forecast in the operation of electric utilities and the features required in these load forecasting algorithms have dictated these research objectives. These objectives have been represented by:

- A rule-based load forecasting for 168-hour load foresting is needed as a part of a load forecasting expert system that can be a part of a generation control system. The main need for the 168-hour rule-base load forecast is for the unit commitment operation problem possibly combined with storage generation. The rule-based approach is believed to have the capability and flexibility of producing load forecasts that are adaptive to changes in the operation of electric utilities and the conditions affecting these operations.

- Combination of rule-based and statistical load forecasting approaches for 7-day lead time would be beneficial. The reason behind this has been addressed from different aspect of benefits. For the problem at hand, this combination could be used to:

  (i) Adjusting the data base that will be used in building the statistical load forecast model or models. This can be done by filtering the effect of the variables that are not accounted for using these statistical techniques.

  (ii) Adjusting the data base from other bad data that can result in building inaccurate load forecast model and replace these data by proper values so that a more accurate load forecast model can be constructed from the same historical data structure.

  (iii) Removing the effect of any enforced actions as applied by the system operator to make the load series as natural as possible and consequently increasing the likelihood of having more accurate forecasts.

  (iv) Modifying the issued forecasts to account for any future conditions that are not considered in building the load forecast model. This includes both external and internal factors to the system.

Chapter IV

EXPERT SYSTEMS AND THEIR APPLICATIONS

4.1 Introduction

Artificial intelligence (AI) is a branch of computer science concerned with the development of intelligent computer programs. Expert systems are fruitful results that have been achieved as a product of applied artificial intelligence in the last twenty years.

Since rule-based expert systems will be applied to the load forecasting problem, a logical step in proceeding towards this goal is by exploring what an expert system is. This starts by defining and explaining the features of an expert system as covered in Section 4.2. This gives an idea about what kind of problems an expert system is suitable for solving. The need for using expert system for these applications is covered in Section 4.3. The architecture of an expert system is next explained in Section 4.4. This includes explanations for each of the components forming the structure of an expert system. Section 4.5 covers an explanation for the characteristics of an expert system. Section 4.6 covers an explanation for the types of activities an expert system can be applied to. These activities are categorized and explained accordingly. Expert systems in the area of power system applications are covered in Section

4.7. Rules of computer languages in designing expert systems and expert system shells are explained in Section 4.8. This is followed by a discussion of rule-based programming in section 4.9. Finally, a summary for this chapter is included in Section 4.10.

4.2 Definition and Features of an Expert System

An expert system is a knowledge-based approach in solving problems in a specific problem area. This means an extensive body of knowledge about the problem domain is needed. This body of knowledge has to be ordered as a collection of rules in order for the system to establish conclusions about the involved problems from this given data.

A formal definition, which reflects the features of an expert system, has been proposed by the British Computer Society's Specialist Group as follows:

> "An expert system is regarded as the embodiment within a computer knowledge-based component, from an expert skill, in such a form that the system can offer intelligent advice or take an intelligent decision about a processing function. A desirable additional characteristic, which many would consider fundamental, is the capability of the system, on demand, to justify its own line of reasoning in a manner directly intelligent to the enquirer. The style adapted to attain these characteristics is rule-based programming" [86].

A simple and brief definition for an expert system is that it is a computer program (though not necessarily algorithmic) which has the ability to act as an expert. This means this program can reason, explain, and have its knowledge-base expanded as new information becomes available to it.

Forsyth [86] has summarized the features that distinguish an expert system as follows:

(1) An expert system is limited to a specific domain of expertise.

(2) It can reason with uncertain data.

(3) It can explain its train of reasoning in a comprehensive way.

(4) Facts and inference mechanism are clearly separated.

(5) It is designed to grow incrementally.

(6) It is typically a ruled-based.

(7) It delivers ADVICE as its output.

(8) It makes money.

4.3 Need for an Expert System

An expert system is needed in cases where features of the problems involved are suitable for its application. The suitability of these applications is based on general experience in the field of application of expert systems. These applications include the following cases [87]:

1. The problems involved need diagnosis rather than calculations as in the operation of many diagnostic systems. This gives a feeling of the different possibilities of diagnostic factors and solutions among which the best can be chosen.

2. The theory governing the involved problem is not completed (has not been established) or is inconsistent. This enables a skilled practitioner to depend on knowledge and "intuition" in solving the problem involved.

3. The human experience about the involved problem (area) is scarce or expensive. Then use of an expert system with a trained person in the field can compensate for the lack of an expert in the field.

4. The data collected to solve the involved problem is " noisy". A tuning logic can come into play by using an expert system.

4.4 Architecture of an Expert System

There are four components by which expert systems are constructed as shown in Figure 2. These components are as follows:

4.4.1 Knowledge Base

A knowledge base consists of facts (or assertions) and rules (or knowledge relationships). Facts represent "declarative knowledge about a particular problem being solved and the current state of affairs in the attempt to solve the problem" [88]. This data can be represented by many methods such as the first-order predicate logic, the frames, or the semantic networks. Rules, on the other hand, represent "formulas showing the relationship among several pieces of information" [89]. A well-known formula for representing rules is the IF-THEN production rule.

4.4.2 Inference Engine

There are two inference strategies that can be used with expert systems. A forward chaining which involves reasoning from data to hypothesis. While a backward chaining involves finding data to prove or disprove the hypothesis. For a successful expert system, both of the fore mentioned strategies have to be implemented.

Besides the above search strategies, the inference engine should contain an explanation trace. This is very important in expert systems because there may be some doubts about the

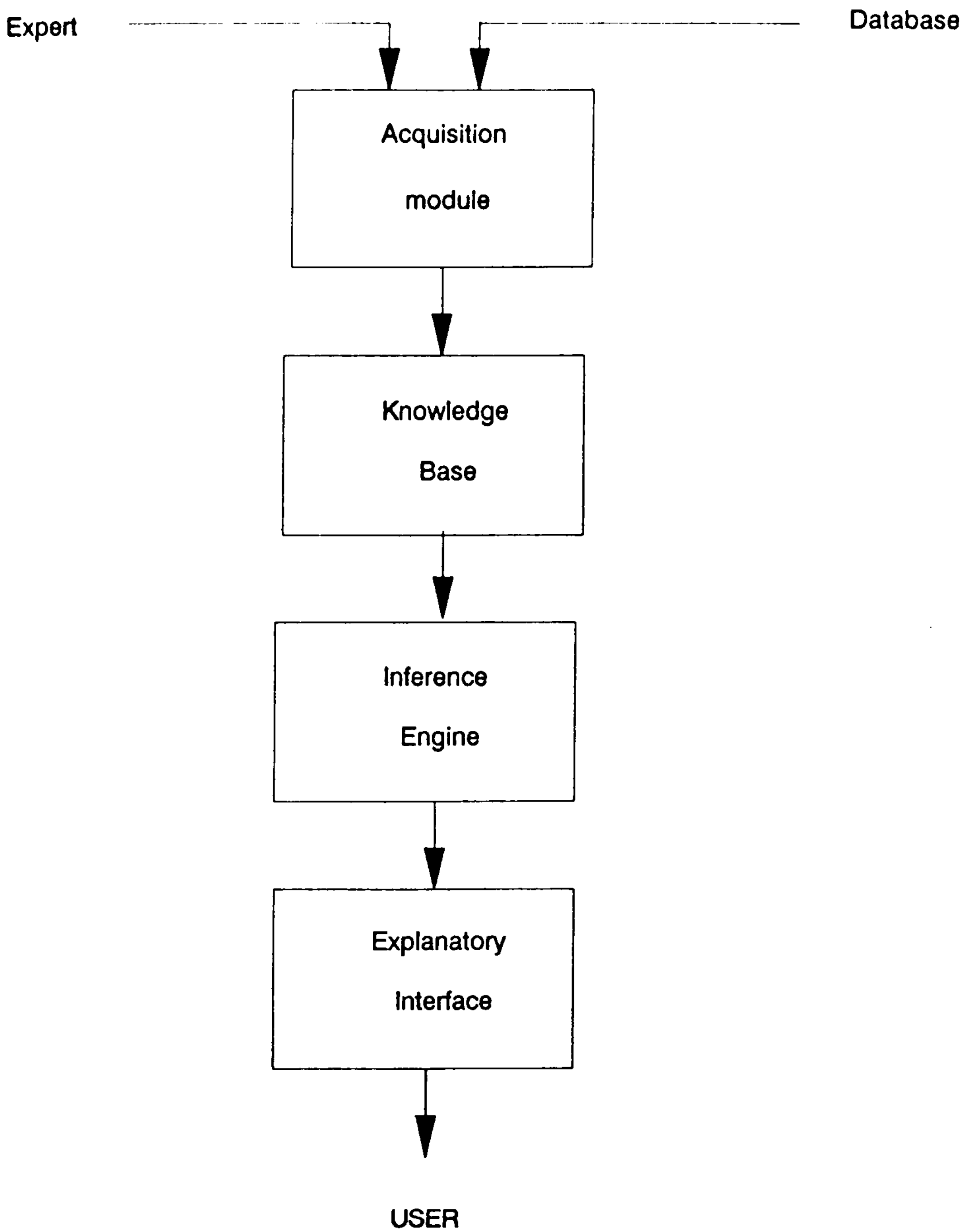


Figure 2. Components of an Expert System.

accuracy of the conclusions drawn by the expert system. Therefore, it is for the systems credit to be able to explain the reasoning that led to the drawn conclusions.

4.4.3 Acquisition Module

Knowledge about the specific problem domain (or expertise) needs to be transferred from the knowledge source (or expert) to a program. This process is costly because of the scarcity of knowledge (or expertise). Usually a "domain expert" (or more) with a "knowledge engineer" are needed in order to codify what the expert knows. This includes the processes in the domain, the general methods for the problem solving, the specific classes of the problem in the domain with the specific methods to solve them.

4.4.4 Explanatory Interface

An expert system needs to be able to reason its own processes if it is asked. This feature of explanation ability is usually done by tracing the reasoning steps that led to the drawn conclusions.

4.5 Characteristics of an Expert System

In order to distinguish an expert system from a conventional program, expert system must have the following characteristics. One of these characteristics and most important is expertise. This is reflected by a good, skillful, and robust performance of the expert system. Another characteristic is symbolic reasoning. This is reflected by a symbolic representation for knowledge and also by symbolic formulation of the problem. A third characteristic of expert systems is depth. This is reflected by the ability of the expert system to handle difficult problems and also by the ability to implement complex rules to solve these problems. A fourth and final characteristic of an expert system is self-knowledge. This is reflected by the ability of the expert system to examine its own reasoning and to explain its operation.

4.6 Activities of an Expert System

Expert systems can be built to solve different problems in different fields. The main activities of an expert system as demonstrated from applications in the power system area are categorized into the following:

1. INTERPOLATION: Interpolation in expert systems is performed by using observables such as sensors in order to infer the description of the system status. This type of activity may need the processing of many different types of data. An example of interpolation expert system is a military interpretation system which uses signals from radar, radio, and sonar devices in order to identify targets and determine their situations.

2. PREDICTION: Prediction in expert systems is performed by simulating models in order to create a scenario that may exist from specific input data. This type of activity may need reasoning about time. An example of a prediction expert system is the one proposed in this work for solving the problem of load forecasting of electric power demands.

3. DIAGNOSIS: Diagnosis in expert systems is performed by using methods or processes that can help in finding the faults of the system. This type of activity may require an interactive course between the user and the system to find the faults and the steps towards correcting them. This activity is the most applied area of power systems to the approach of expert systems. An example of a diagnostic expert system is a hybrid expert

system for identification of faulted sections and interpreting protective apparatus' operation in large interconnected power systems [91].

4. DESIGN: Design is performed by the development of the shape and structure of objects. This development is confined by meeting the required characteristics without violating the problem constraints. Design is usually associated with another activity, planning. An example of a design expert system is the application of intelligent computer-aided design techniques to power plant design and operation [92].

5. PLANNING: Planning is performed by the design actions. This means decision comes before design. Planning is usually associated with back tracking or rejecting part of the plan where violation of limits occurs. An example of a planning expert system is an intelligent support system for power system planning [93].

6. MONITORING: Monitoring is performed by comparing the actual and the predicted behavior of the system. This is done by observing events that agree with the expectations about a particular behavior. Monitoring deals with time which should be implemented in the interpretation of the monitoring results of the system. An example of monitoring expert system is a dispatcher alarm and message processing system [94].

7. DEBUGGING: Debugging is performed by suggesting corrections for the existing faults. This is done by using tables of remedies which correspond to specific faults. A difficult task in debugging is the design of effective remedies by the system. An example of a debugging expert system is an expert system that act as an aid for the system dispatcher for the isolation of line section faults [95].

8. REPAIR: Repair is performed by developing and executing prescribed remedies for some known faults. This is done by implementing the capabilities existing in the debugging and

planning activities in the process of repair execution. An example of a repair expert system is a KBES (knowledge-based expert system) for power system restoration [96].

9. INSTRUCTION: Instruction is performed by the embodiment of debugging, repair, and diagnosis activities to problems addressed to students. Such systems are built to diagnose the deficiencies in the student's knowledge and find suitable remedies for them. An example of an instruction expert system is the EPRI (electric power research institute) operator training simulator [97].

10. CONTROL: Control is performed by governing the overall behavior of the system. This is done by coordinating many activities at the same time such as monitoring, diagnosis, debugging, planning, and prediction. A good example for a control expert system is an expert system for assisting decision making of reactive power/voltage control [98].

4.7 Expert Systems Applied to Power Systems

In the last section the different activities of expert systems have been categorized with an explanation for each category. Many of these categories, that have been explained, are performed by engineers in the power system area. Many of these activities are good candidates to the application of expert systems as demonstrated by examples from the power system area in the last section.

Interest for the application of expert systems in the power engineering area has increased greatly in the last years. This interest is mainly due to the fact that expertise plays an important and integral role in many aspects of power system operations. Also, this interest is growing due to the facts that experts are scarce. Such scarcity is a result of the long period required for new experts to emerge as a result of retiring of existing experts at sometime in their life. This makes expert systems viable solution to many of the problems in the power system area. Mainly, they can be used as an aid to the decision making and as a buffer to minimize the operators' human error.

Most of the interest in the applications of expert system in the power system was led by the Electric Power Research Institute (EPRI). Such interest was aimed to develop expert systems for the existing electrical power systems. At present, application of expert systems has spanned many aspects of the power system operations as surveyed by Zhang [87]. These aspects include the following:

- Fault diagnosis
- Load flow planning
- Reactive power and voltage control
- Switching operations
- System restorations
- Security assessment
- Transient stability problem
- Unit commitment
- Operator training
- Friendly interface
- Network maintenance scheduling
- Substation automation
- Computer relaying
- HVDC transmission system
- Utility electrical power plants systems

Some applications of the activities in the power system area have been mentioned in the previous sections. Other applications could be found in the work reported in the references [99] through [102]. References to other different aspect of applications that are mentioned above could be found in the work of Zhang et. al. [87]. This is the most recent work that gives a bibliographical survey on expert systems in the electric power system area.

4.8 Programming Languages and Expert System Shells

An expert system is an intelligent computer program with some distinguished features. This means that the tools for building such a system are programming languages. There are two types of programming languages. One type is problem-oriented languages such as APL, FORTRAN, and PASCAL. These types of languages are capable of conveniently performing algebraic calculations. This makes these types suitable for the application to problems in the fields of science, mathematics, and statistics. The other type is symbol-manipulation languages such as OPS (a rule-based language), LISP (a procedure-oriented language), and PROLOG (a logic-based language).This type is suitable and useful when complex concepts are required for representation. LISP is the most popular language used in the application of an expert system. In spite of the popularity gained by PROLOG, this language is "ahead of its time" as described by Forsyth [86]. However, a recent survey of application of expert systems in the power system area shows that PROLOG applicability is increasing [87]. Almost equal applications are attributed to both LISP and PROLOG at the current state. Applications using OPS are less than that of either LISP or PROLOG applications. Many of the applications using OPS are in different versions such as OPS5 and OPS83.

The application of expert systems to a specific domain area usually incorporates building all the components of an expert system previously discussed in section 4.3. This means building the interface, inference engine and the knowledge base components. Some expert systems are built such that they are suitable to work in different field domains. Such systems are build without the knowledge-base component. These systems are referred to as expert system shells. These can be applied to the different suitable domains by constructing the appropriate knowledge-base of such domains.

4.9 Rule-Based Programming

Most current expert systems are described using rule-based techniques. The rule-base represents the set of rules that governs the behavior of the system. These rules are usually called production rules. The basic form for representing these rules is the IF-THEN production rules. This means that for the actions under the THEN statement to be appropriate, all the conditions under the IF statement must be true.

The rules in the data base can be represented either in the problem-oriented languages such as FORTRAN and PASCAL or symbol-oriented languages such as LISP and PROLOG. Usually the symbol-oriented languages (known as rule-base languages) are suitable for large data bases where numerous rules have to be represented. Besides, the symbol-oriented languages are more open in the sense that new rules can be added easily.

4.10 Summary

This chapter has covered most of the concepts associated with expert systems. This includes definition and features, suitability for applications, architecture, activities, and applications in the power system area of expert systems. The role of programming language and expert system shells, and rule base programming are discussed. This coverage has been a necessary step before proceeding to the topic of this dissertation which includes implementation of expert systems to load (demand) forecasting.

Chapter V

TIME SERIES APPROACH TO LOAD FORECASTING

5.1 Introduction

Time series are sets of discrete or continuous observations in time. These observations are usually sampled at equidistant time intervals. Depending on the nature of future values, there are two classes of time series. These are the deterministic and the stochastic time series processes. In the deterministic time series process, the future values of the time series are known exactly by means of exact formulation. On the other hand, the future values of the stochastic time series can only be known in terms of probability distribution functions.

The nature that governs the electrical load is a stochastic process. Therefore, the concern in this part of the study will be focused on the stochastic time series approach.

5.2 Classes of Stochastic Time Series Processes

Time series are classified into stationary or nonstationary processes. For a time series process to be categorized as a stationary process, it has to satisfy the two conditions of stationary. These two conditions are:

1. The mean of the time series has to be constant with time, i.e.,

$$E\,(y(t)) = constant \tag{5.1}$$

2. The covariance between any two equidistant observations (in time) is a function of the relative time distance only, i.e.,

$$\text{cov}\quad (y(t+k),\, y\,(t)) = \quad \text{cov}\quad (y(t+k+n),\, y(t+n)) \tag{5.2}$$

In reality, many of the time series are classified as non-stationary processes. Since stationary time series are the only processes that can be modeled, transformation of these time series into stationary processes are needed. This can be achieved for many of the nonstationary time series in the following cases.

1. If the mean of the time series is changing, then differencing the time series one time or more could produce a stationary process. In this case, the differenced time series will be modeled instead of the original series. This subject is discussed in section 5.3.3 under modeling the class of autoregressive integrated moving average (ARIMA) processes.

2. If the variance of the time series is changing with time, a suitable transformation can be found for some of these processes. For example, if the variability is constantly increasing with time a logarithmic transformation can suppress this variability and the process could be transformed into a stationary one along with performing step 1 if needed.

5.3 Modeling

A stochastic time series can be represented as shown in Figure 3. In this representation, the time series y(t) is modeled as the output from linear filter. The input to this filter is a series of random "chocks", a(t) [22]. This random input is of zero mean and unknown fixed variance $\sigma_a^2(t)$ (i.e., a white noise).

Depending on the characteristic of the linear filter, different models can be classified as follows:

5.3.1 The Autoregressive (AR) process

In the autoregressive process the current value of the time series y(t) is expressed linearly in terms of its previous values, y(t-1), y(t-2), .., and a random white noise, a(t). The order of this process depends on the oldest previous value at which y(t) is regressed on. For an autoregressive process of order p (i.e., AR(p)), this model can be written as:

$$y(t) = \phi_1 y(t-1) + \phi_2 y(t-2) + \ldots + \phi_p y(t-p) + a(t). \tag{5.3}$$

A convenient way to express the previous equation can be obtained when introducing the following backshift operator:

$$By(t) = y(t-1);$$

$$B^2 y(t) = y(t-2);$$

and

$$B^m y(t) = y(t-m) \tag{5.4}$$

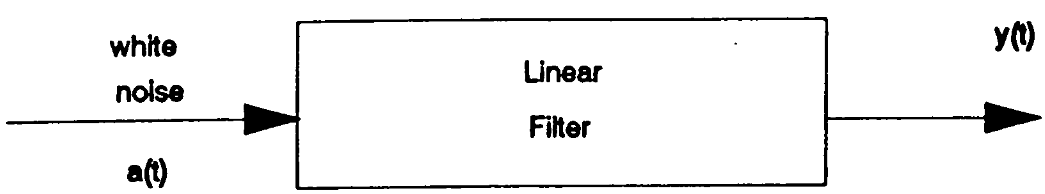


Figure 3. Description of a Time Series as the Output of Linear Filter Whose Input Is a White Noise.

It can be easily verified that equation (5.3) can be written by using the operator expressed in equation (5.4) as follows:

$$\phi(B)y(t) = a(t). \tag{5.5}$$

where,

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p. \tag{5.6}$$

The parameters expressed in equation (5.6) are chosen such that the autoregressive process is stationary. This means that the system is stable. In other words, when expressing equation (5.5) in transfer function form, the poles of this transfer function are all located within the unit circle. The identification of the autoregressive process parameters is based on the spectrum of the autocorrelation function (ACF) and the partial autocorrelation function (PACF). This method is covered in section 5.4.1.

The estimation of the AR parameters are obtained from the sample ACF. This solution for the estimates of the parameters of the AR process is known as the Yule-Walker equations solution. A discussion of the estimation method is covered in section 5.4.2.

5.3.2 The Moving-Average (MA) process

In the moving-average process, the current value of the time series y(t) is expressed linearly in terms of current and previous values of a white noise series. The order of this process depends on the oldest value of this noise series at which y(t) is regressed on. For a moving average of order q, (i.e., MA(q)), this model can be written as:

$$y(t) = a(t) - \theta_1 a(t-1) - \theta_2 a(t-2) - \dots - \theta_q a(t-q). \tag{5.7}$$

A similar convenient form to write equation (5.7) can be obtained by applying the backshift operator on the white noise terms as follows:

$$Ba(t) = a(t-1);$$

$$B^2a(t) = a(t-2);$$

and

$$B^n a(t) = a(t-n). \tag{5.8}$$

Using the operator expressed in equation (5.8), it can be easily shown that the MA(q) can be written in the form:

$$y(t) = \theta(B)a(t). \tag{5.9}$$

where,

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q. \tag{5.10}$$

The parameters expressed in equation (5.10) are chosen based on the assumption that the process is invertible. This means that the input, i.e., the white noise, can be known completely in terms of the output. This also means all the zeros of equation (5.10) are located within the unit circle. The identification of and estimation of the moving-average process parameters is explained in section 5.4.1, and section 5.4.2 respectively.

5.3.3 The Autoregressive Moving-Average (ARMA) process

In the autoregressive moving average process, the current value of the time series y(t) is expressed linearly in terms of its values at previous periods and in terms of current and previous values of a white noise series. The order of the ARMA process is selected by both the oldest previous value of the load series and the oldest previous value of the white noise series at which y(t) is regressed on. For an autoregressive moving-average process of order p, and q (i.e. ARMA(p,q)), the model is written as:

$$y(t) = \phi_1 y(t-1) + \ldots + \phi_p y(t-p) + a(t) - \theta_1 a(t-1) - \ldots - \theta_q a(t-q). \tag{5.11}$$

By using the operator defined in equation (5.4) and equation (5.8), it is clear that equation (5.11) can be written in the following form:

$$\phi(B)y(t) = \theta(B)a(t). \tag{5.12}$$

where ϕ(B) and θ(B) are defined by equation (5.6) and equation (5.10) respectively.

As mentioned earlier, the parameters of AR and MA processes are chosen such that these processes are stationary and invertible respectively. For the ARMA process these conditions must be satisfied. Together this means that all the pole and zeros of the transfer function of equation (5.12) are located within the unit circle. The choice of the ARIMA parameters and their estimation are covered in section 5.4.1 and section 5.4.2 respectively.

5.3.3 The Autoregressive Integrated Moving-Average (ARIMA) process

In modeling time series in the previous sections as an AR, MA, or as an ARMA processes, it has been assumed that these series are stationary according to the definition given in section 5.2. Therefore, if the process is nonstationary, transformation of the series to a stationary process has to be performed first. This can be achieved to many time series by a differencing process. By introducing the ∇ operator, a differenced time series of order 1 can be achieved as:

$$\nabla y(t) = y(t) - y(t-1). \tag{5.13}$$

By using the operator defined in equation (5.6), equation (5.13) can be written in the form:

$$\nabla y(t) = (1 - B)y(t). \tag{5.14}$$

A cascade differencing of order d can be written using equation (5.14) as:

$$\nabla^d y(t) = (1 - B)^d y(t). \tag{5.15}$$

The resulted differenced series, $\nabla^d y(t)$ obviously has less observations than the undifferenced time series, y(t), equal to the degree of differencing, d. The model for an autoregressive integrated moving-average of degree p, d, and q ,(i.e ARIMA(p,d,q)), is written as:

$$\phi(B)\nabla^d y(t) \; = \; \theta(B)a(t). \tag{5.16}$$

where ϕ(B), ∇^d, and θ(B) are defined by equations (5.6), (5.10) and (5.15) respectively.

The choice of the parameters of the differenced series and their estimation is performed in the same manner as that of an ordinary ARMA process.

5.3.4 Seasonal processes

As a result of daily, weekly, yearly or other periodicities, many time series exhibit periodic behaviors in response to one or more of these periodicities. Therefore, a different class of models which have this property is designated as seasonal processes. Seasonal time series could be modeled as an AR, MA, ARMA or an ARIMA seasonal process similar to the nonseasonal time series discussed in the previous sections [22]. A purely ARIMA seasonal process is written as:

$$\Phi(B^s)\nabla_s^D y(t) = \Theta(B^s)\alpha(t) \tag{5.17}$$

where,

$\alpha(t)$ = a noise series

$$\Phi(B^s) = 1 - \Phi_1 B^s - \ldots - \Phi_P B^{Ps}$$
$$\Theta(B^s) = 1 - \Theta_1 B^s - \ldots - \Theta_Q B^{Qs}$$
$$\nabla_s^D = \text{seasonal difference operator.}$$

It is rare to find a model which is purely seasonal. In other words, the series $\alpha(t)$ has to be a white noise. Therefore, another filter is needed to model the nonseasonal effect contained in $\alpha(t)$. The ARIMA process for $\alpha(t)$ can be written using equation (5.16) as:

$$\phi(B)\nabla^d y(t)\alpha(t) = a(t) \tag{5.18}$$

Combining equation (5.17) and equation (5.18) gives the so called general multiplicative model [22].

$$\Phi(B^S)\phi(B)\nabla^d\nabla_S^D y(t) = \Theta(B^S)\theta(B)a(t) \tag{5.19}$$

If higher periodicities exist, similar procedures can be used to drive the multiplicative model which will be structured similar to equation (5.19).

5.3.5 Transfer function modeling

The previous models allow y(t) to be expressed in terms of its history (and a white noise). If other variables are affecting the value of y(t), inclusion of the effect of these variables can be accounted for using a transfer function model. For the case of one independent variable x(t), the transfer function model shown in Figure 4 can be written in the form [22,103].

$$y(t) = \frac{\omega(B)}{\sigma(B)} X(t-b) + n(t) \tag{5.20}$$

where,

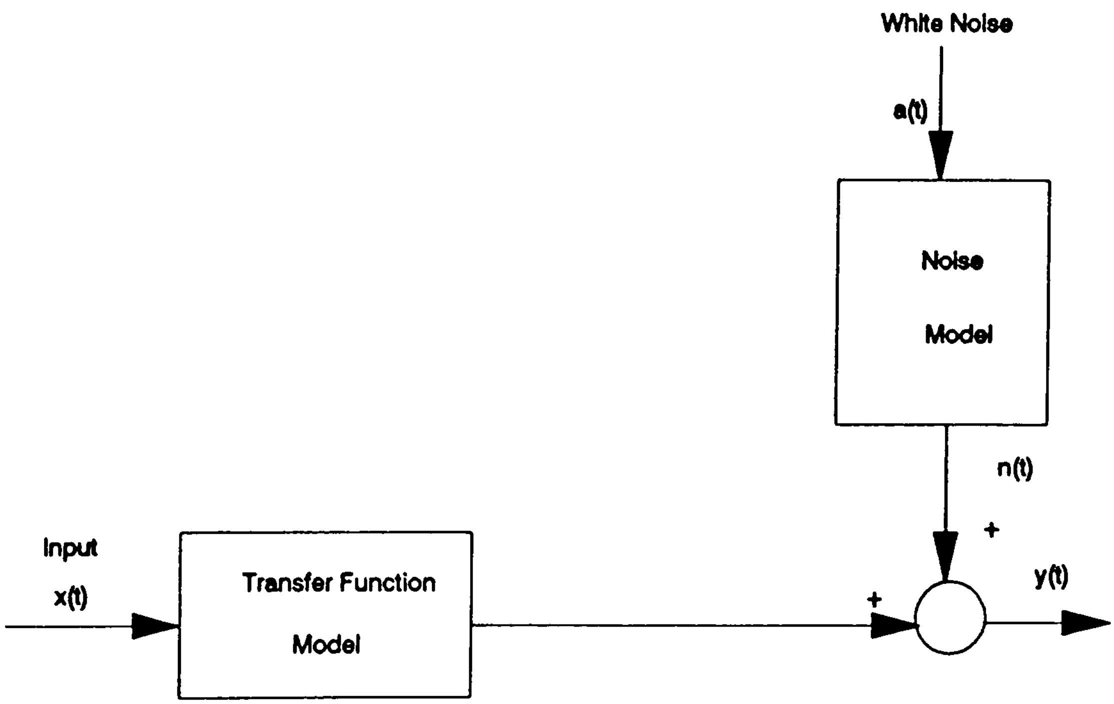


Figure 4. Transfer Function Load Modeling

ω (B) = polynomial of order r.

σ (B) = polynomial of order s.

x (t-b) = weather variable leading the response by b time intervals.

n (t) = a non-white noise series.

The series n(t) can be modeled in terms of its past values and a white noise using any of the previously discussed processes. The response lag time b and the orders r, s of the $\omega(B)$ and $\sigma(\omega)$ polynomials can be identified from the cross correlation function plot between the stationary (and prewhitened) y(t) and x(t) series. A preliminary estimate of the parameters of the polynomials $\omega(B)$ and $\sigma(B)$ can also be found from the cross correlation values once b, r, and s are identified.

5.4 The Box-Jenkins Methodology

Box and Jenkins [22] have introduced a complete and systematic method for forecasting and control of time series. This is the most popular and accurate method among the ones that have been used by many electric power utilities. The Box and Jenkins methodology is an iterative procedure consisting of three stages as shown in Figure 5. These stages are the identification, estimation, and diagnostic checking for the model. A discussion of each of these stages and the model overfitting is discussed repectively in the following subsections.

5.4.1 Identification

The identification of the load forecasting models is obtained by analyzing the raw load data. This analysis includes the use of the range-mean ,autocorrelation function, and partial autocorrelation function plots. The use of these tools leads to initial guesses of the required

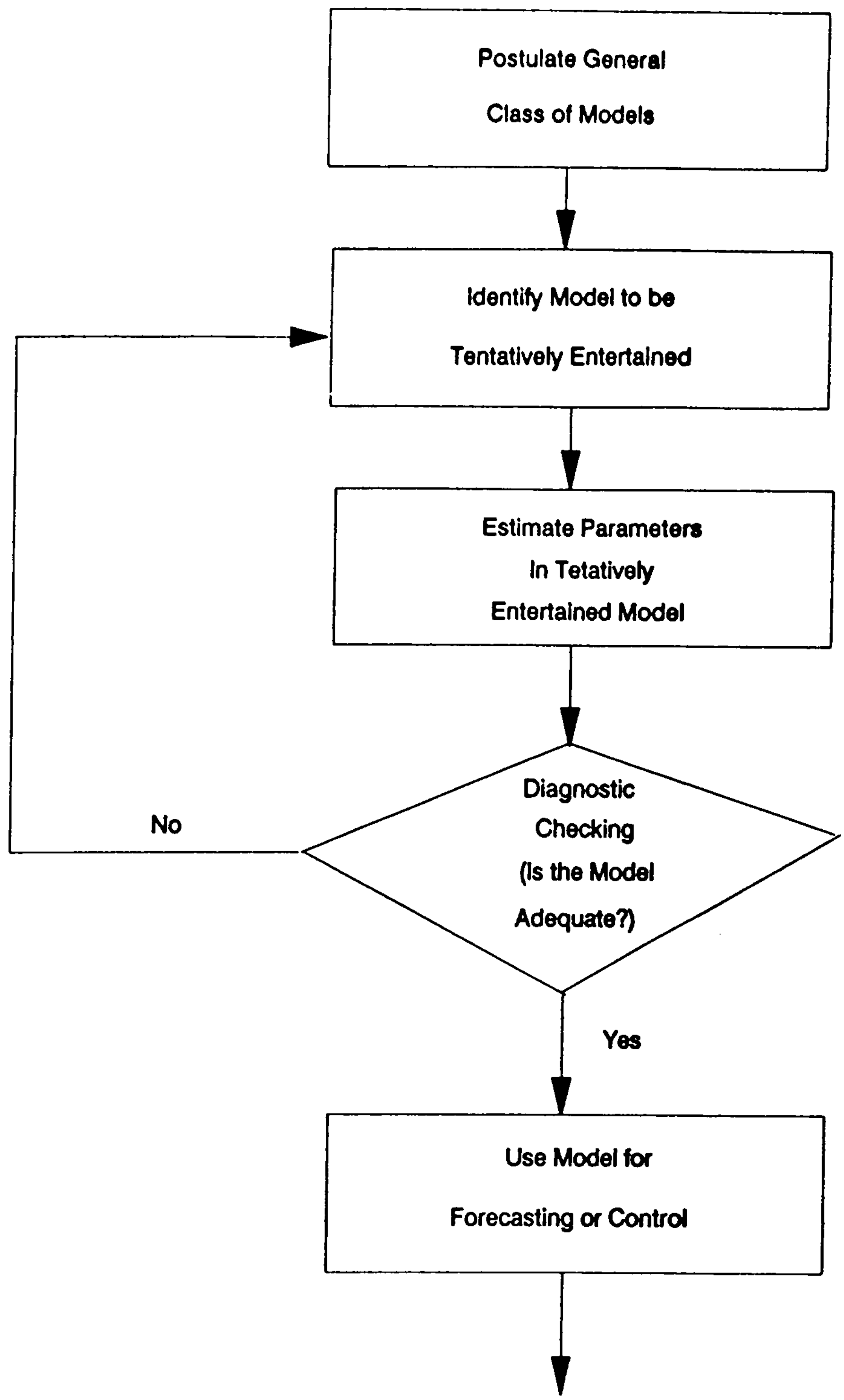


Figure 5. Procedure of the Box and Jenkins Methodology.

data transformation and degree of differencing to obtain a stationary process. Besides, the order of the polynomials appearing in the autoregressive (AR) and the moving-average (MA) parts of the series can be initially identified [103]. The degrees of the AR and the MA polynomials are determined by means of using the autocorrelation function (ACF) and the partial autocorrelation functions (PACF) according to the following rules [104].

- If the ACF of the series is of infinite length while the PACF of the series is of finite length then the series is modeled as an autoregressive process of order p. This process order is equal to the length of the PACF and this process is defined as AR(p).

- If the length of the PACF of the series is infinite while the length of the ACF is the series is finite then the series is modeled as a moving average process of order q. This order is obtained as the finite length of the ACF and the process is defined as MA(q).

- If the both the ACF and the of the series are of infinite lengths, then the series is modeled as autoregressive moving-average process of orders p,q and defined as ARMA(p,q).

5.4.2 Estimation

The estimation of the parameters of the identified load forecasting model is usually achieved through the use of an efficient estimation method. For a pure AR model the Yule-Walker equation solution results in the estimates of the parameters of this process. Other methods such as the maximum likelihood technique are capable of being applied to other processes as well. Along with the estimation of the load forecasting model estimation of the standard deviation and correlation of these parameters along with the variances and covariances of the residuals are established for the analysis [103].

5.4.3 Diagnostic checking

The load forecast model obtained can only be assumed correct as identified with its parameters as estimated only if such model passes the diagnostic checking test. This step is usually performed to account for any inadequacies in the model obtained. Such inadequacies could exist as a result of the lack of the model to account for all needed explanatory variables.

The residual autocorrelation function (ACF) and partial autocorrelation function (PACF) provide a sufficient evidence whether the assumed model is elaborated. If the model is not adequate then the ACF and PACF of the residuals give indications about the source of these inadequacies. If correction is suggested in the diagnostic test then it is implemented and the estimation stage is reexecuted and the diagnostic checking is performed. This iterative procedure continues until adequate load forecasting model is obtained.

5.4.4 Over-fitting

Over-fitting is a technique that is used for diagnostic checking. Usually it is applied to insure the adequacy of the identified model by accounting for the suspected influential parameters that can help improving the model accuracy. The account of these parameters is performed one parameter at a time. If no further improvement is achieved, this process can be considered as a proof of the correctness of the identified model.

5.5 Summer Load-Forecast Models

The Box and Jenkins methodology discussed in the previous section was used to build stochastic time series forecasting models for the hourly electric load in all seasons. Both the multiplicative seasonal ARIMA and the TF processes were investigated in building these hourly load forecast models. The building and application of such models are presented in this section to the Summer hourly load forecast models as follows:

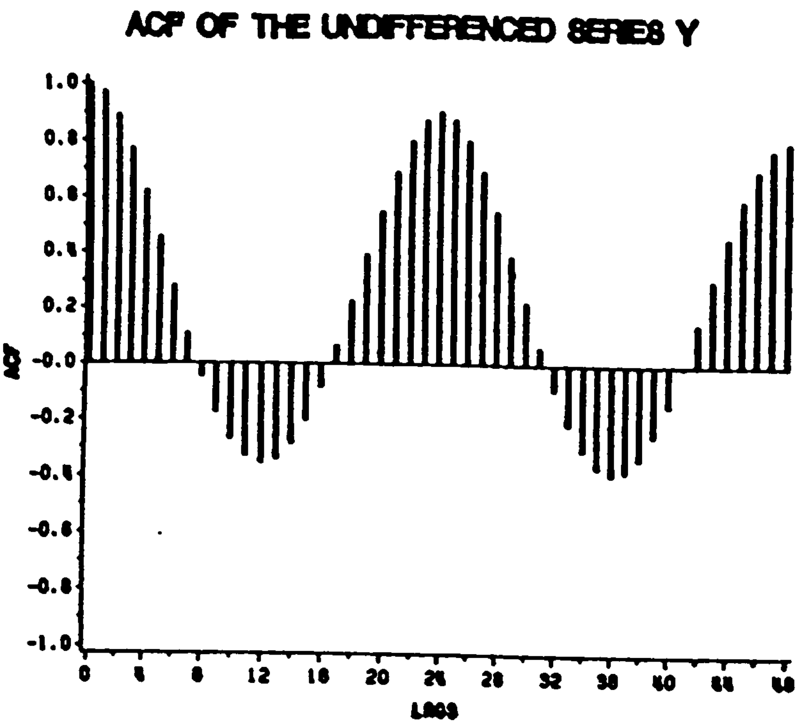
5.5.1 The Multiplicative Seasonal ARIMA Load Forecast Model

This model has been identified using plots of the ACF and PACF of the the hourly load time series using four weeks of hourly load observations. First, the ACF of the original (undifferenced) time series has been plotted as shown in Figure 6. The infinite length of this ACF indicated that the series is not stationary and needs to be differenced. Also, the cyclic autocorrelation shown in the ACF plot indicated that there is a seasonal (daily) effect. Performing a non-seasonal (i.e., hourly) and a seasonal (i.e., daily, $s=24$) differencing to the time series separately and together, the ACF plots using these differenced series have been found as shown in Figures 7(a), 7(b) and 8(a) respectively. The ACF plot in Figure 8(a) indicated that the differenced series, $\nabla\nabla_{24}y(t)$, is stationary. Second, using the ACF and the PACF plots of this differenced series shown in Figure 8 , (a) and (b), and the fact that the model will be used for issuing forecasts upto 168-hour lead time, the best model has been found as:

$$\begin{aligned}&(1-\phi_1 B-\phi_2 B^2-\phi_3 B^3-\phi_{12} B^{12})\\&\quad(1-\Phi_{24}B^{24}-\Phi_{25}B^{25}-\Phi_{48}B^{48}-\Phi_{72}B^{72}-\Phi_{96}B^{96}-\Phi_{120}B^{120}-\Phi_{144}B^{144})\\&\qquad\nabla\nabla_{24}y(t)=(1-\Theta_{168}B^{168})a(t)\end{aligned} \tag{5.21}$$

The above load model has been obtained after several iterations that were based on the minimum standard error which has been estimated as 79.12 (MW).

The estimates of the load model parameters has been found using the conditional least-squares estimation technique. These estimates are shown in Table 3.



MONTH:AUGUST 83
DATA BASE 7/5 TO 7/31/83

Figure 6. The Autocorrelation Function (ACF) of the Summer Hourly Load Time Series, y(t)

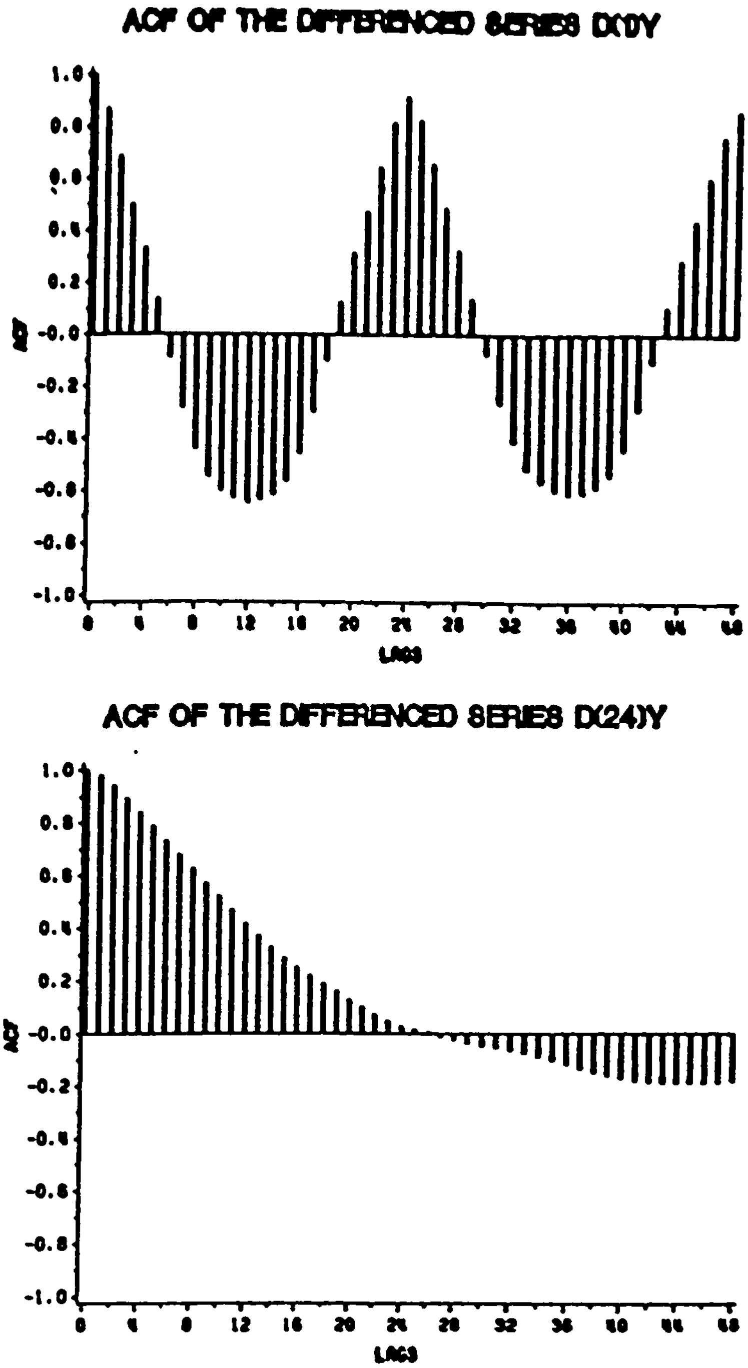
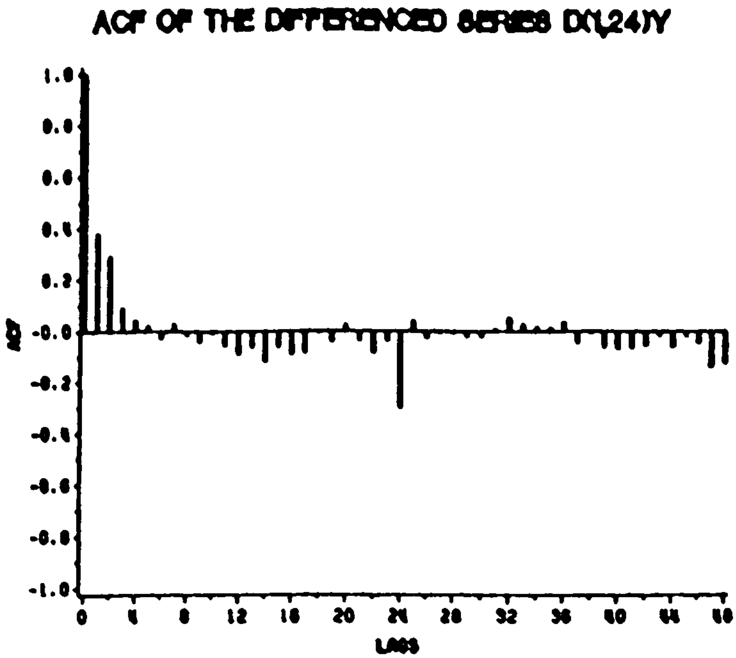


Figure 7. The Autocorrelation Function (ACF) of the Summer Hourly Load Time Series (a) $\nabla y(t)$ (b) $\nabla_{24} y(t)$



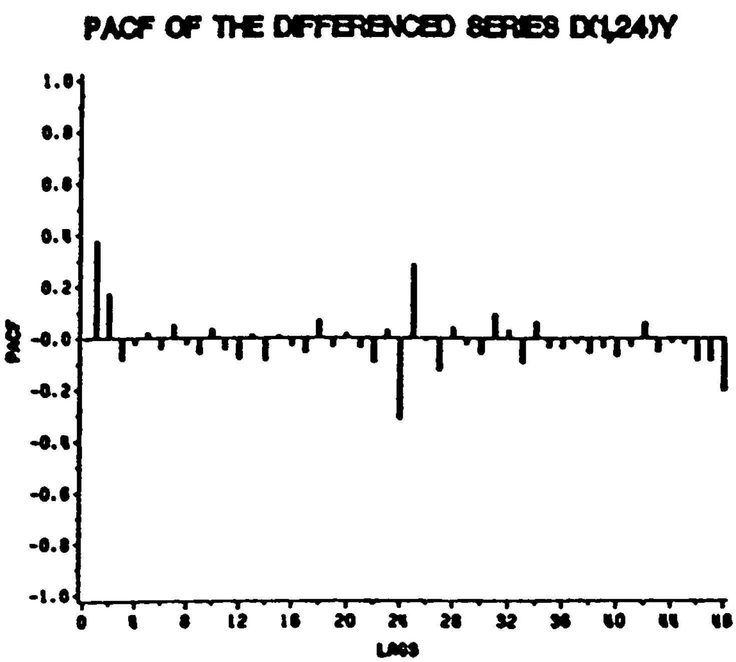


Figure 8. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Summer Hourly Load Time Series, $\nabla\nabla_{24}y(t)$

Table 3. Estimates of the Summer Hourly Load Seasonal ARIMA Model Parameters

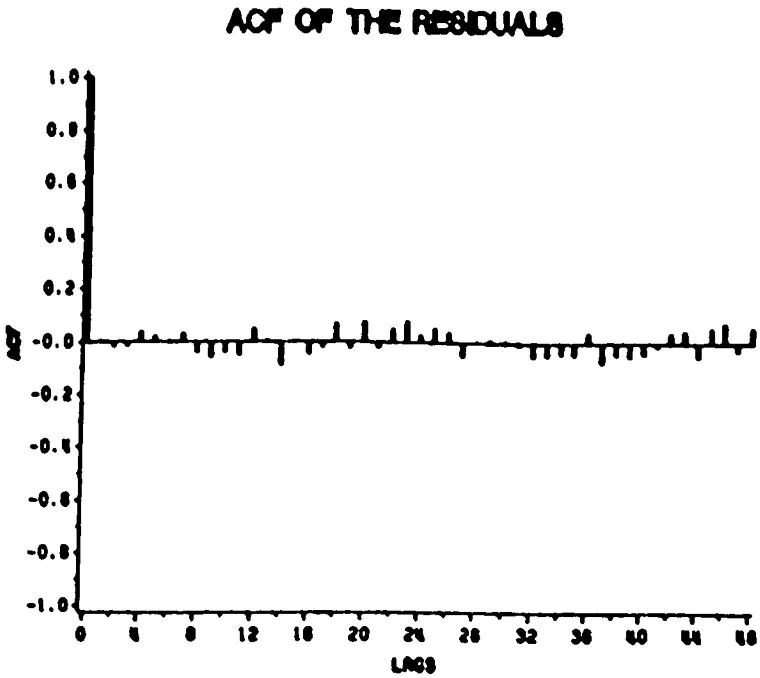
Parameter	Estimate	Approximate Standard Error	T-Ratio
Θ_{168}	0.258353	0.0683212	3.78
ϕ_1	0.360791	0.0404148	8.93
ϕ_2	0.261702	0.0418854	6.25
ϕ_3	-0.102288	0.0400343	-2.56
ϕ_{12}	-0.144239	0.0352276	-4.09
Φ_{24}	-0.774248	0.0380028	-20.37
Φ_{25}	0.109775	0.0299357	3.67
Φ_{48}	-0.696514	0.0464636	-14.99
Φ_{72}	-0.669257	0.0514090	-13.02
Φ_{96}	-0.639803	0.0543695	-11.77
Φ_{120}	-0.715685	0.0553242	-12.94
Φ_{144}	-0.552752	0.0609496	-9.07

The check of the adequacy of this model has been performed by plotting the ACF and the PACF of the residual series as shown in Figure 9(a) and (b). Such plots indicated that the autocorrelation of the noise series is not significant for all lag times and consequently this series is considered as a white noise series.

Hourly load forecasts upto 168-hour lead time have been generated using the Summer model described by equation (5.21) and Table 3. About one week data-depth has been used for generating these forecasts. The hourly load forecasts and the actual hourly load data are shown in Figure 10. The average absolute percent error of these forecasts has been found to be 6 % with respect to the actual hourly load data and as 4.4 % with respect to the actual weekly peak load. These results indicated that about 96 % of these forecasts have absolute forecast errors of less than 10 % with respect to the weekly peak load. Since the forecast error increases as the forecast lead time increases, most of the contribution for the high error indicated above (i.e., 10%) is due to the build up in the inaccuracy of the forecasts as a result of using forecasted values in issuing higher lead time forecasts.

5.5.2 The Transfer Function (TF) Model

The TF model building is also an iterative process using the three stages of identification, estimation, and diagnostic checking. The TF model building requires finding of three models; (i) finding a model for the input variable, (ii) finding a model for the part that can be explained by the input variable, i.e., the input-output transfer function, and (iii) finding a model for the residual series ,i.e., the unexplained part by the effect of the input variable. The Summer TF model has been built assuming that the dry bulb temperature (DBT) is the major input variable that affect the demand for electricity. The hourly DBT data that are associated with the hourly load have been used to build the TF model input variable. In particular, a transformed form for the dry bulb temperature is defined by:



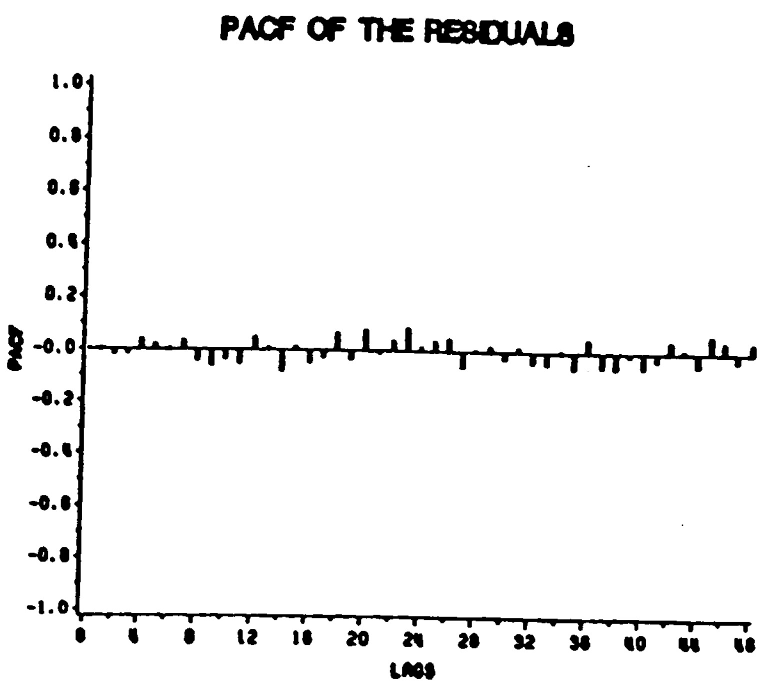
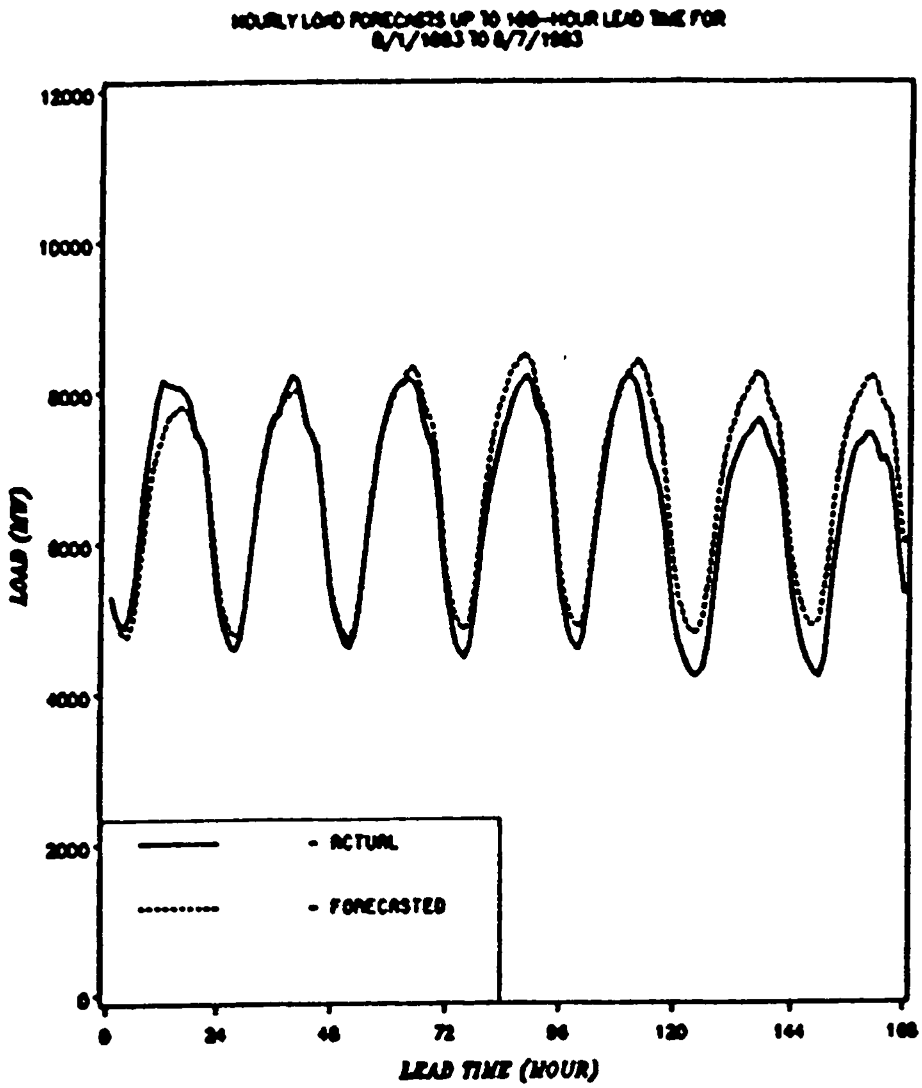


Figure 9. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Noise Series, a(t).



MODEL:D(1,24)(1,2,3,12)(24,25,48,72,96,120,144)Y=(168)A

ALLDAYS DATABASE 7/5 TO 7/31/83

Figure 10. The Actual and Forecasted Hourly Load Data for August 1-7 1983

$$x(t) = \begin{cases} DBT(t) - 72.0 & DBT > 72.0\,F^{o} \\ 0.0 & DBT \leq 72.0\,F^{o} \end{cases} \tag{5.22}$$

The input variable has been chosen as defined by equation (5.22) based on cross-correlation analysis between the load and the DBT which has shown that only small cross-correlation exists at lag zero and no further significant cross-correlation exist at any other lag time. Definitely this is not the case and the choice and defining the input as given by equation (5.22) has resulted in some improvement which needs to be investigated further to obtain the actual effect of the dry bulb temperature.

1. The input variable model has been built using a multiplicative seasonal ARIMA process exactly as performed for building the seasonal multiplicative model for the hourly load data presented in section 5.5.1 as follows. First, the input series has been transformed into a stationary series by performing a non-seasonal (hourly) and a seasonal (daily) differencing operations as shown in the Figures 11 through 13. Second, based of the ACF and the PACF shown in Figure 13 and the fact that the input variable has to be forecasted upto 168-hour lead time in order for the TF model to be able to generate load forecasts upto such lead time, the best model for the hourly input variable (DBT) has been found as:

$$(1 - \phi_1 B)$$

$$(1 - \Phi^{24}B^{24} - \Phi_{48}B^{48} - \Phi_{72}B^{72} - \Phi_{96}B^{96} - \Phi_{120}B^{120} - \Phi_{144}B^{144} - \Phi_{168}B^{168} - \Phi_{192}B^{192})$$

$$\nabla\nabla_{24}x(t) = \alpha(t) \tag{5.23}$$

This model has been obtained after several iterations to determine the highest significant seasonal autoregressive order for this model. The criterion for such determination was based on the standard error of the residuals which has been found as 1.043 (F^{o}).

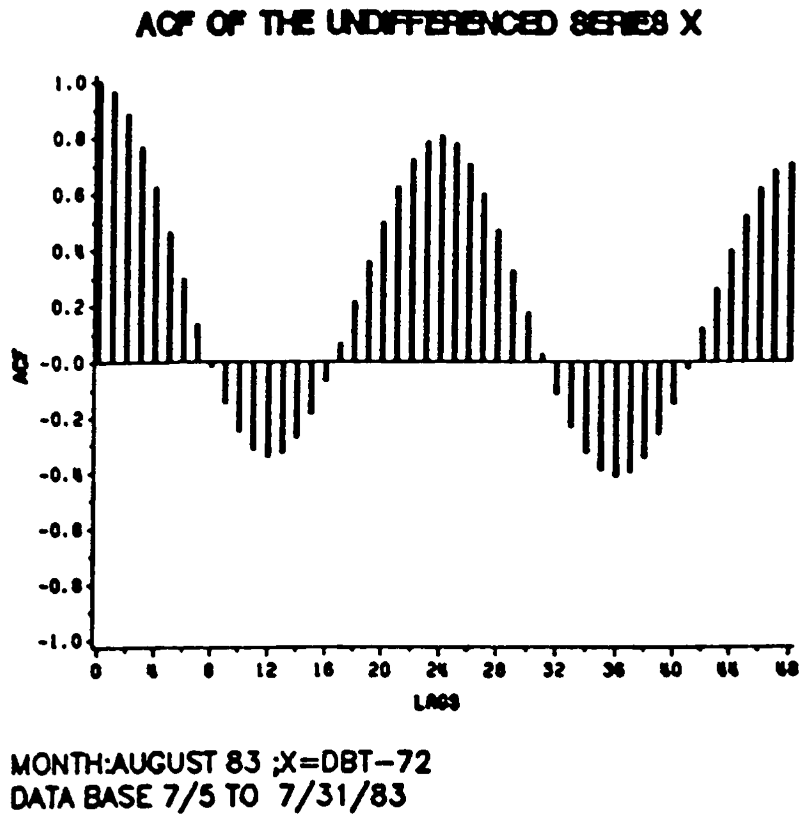


Figure 11. The Autocorrelation Function (ACF) of the Summer Hourly Input Time Series, x(t)

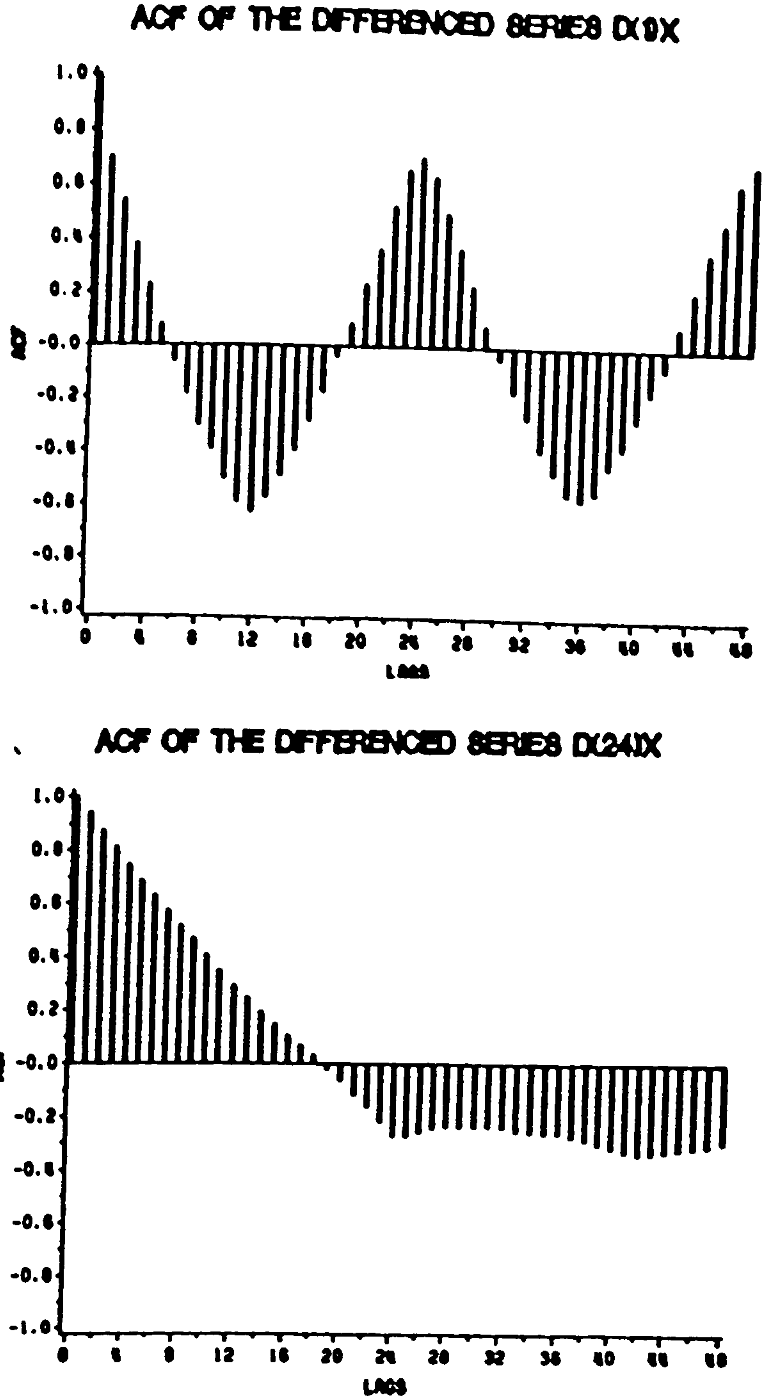
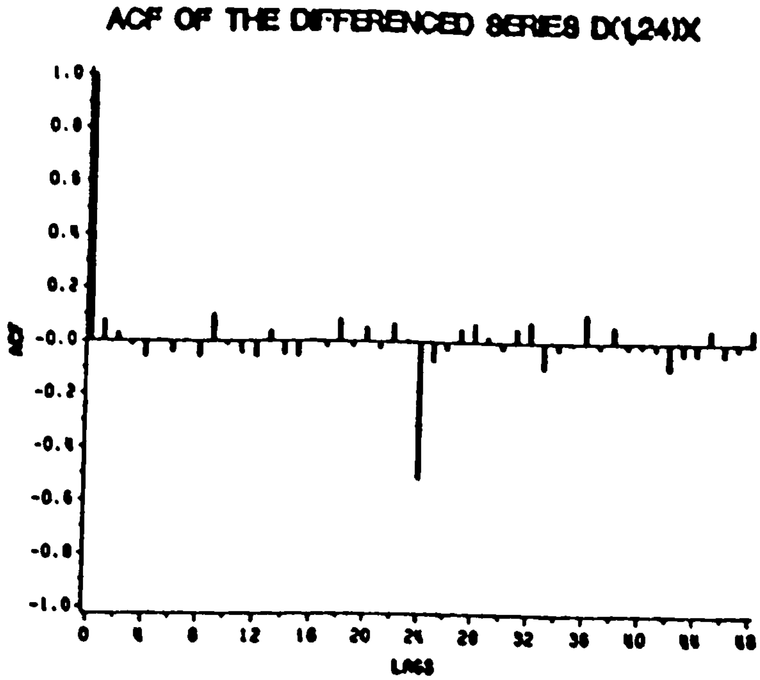


Figure 12. The Autocorrelation Function (ACF) of the Summer Hourly Input Time Series (a) $\nabla x(t)$ (b) $\nabla_{24} x(t)$



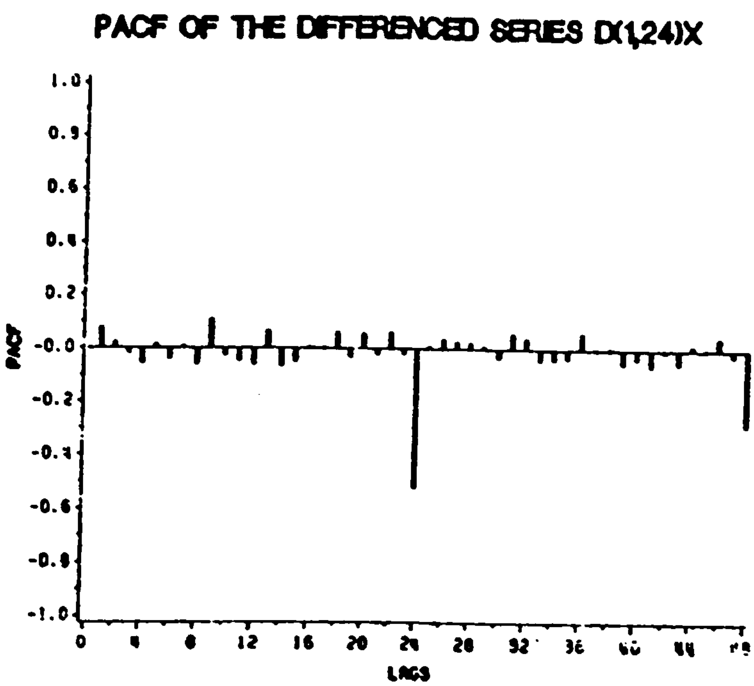


Figure 13. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Summer Hourly Input Time Series, $\nabla\nabla_{24}x(t)$

The estimates of the parameters of the hourly input variable has been found using the conditional least-squares estimation technique. These estimates and are given in Table 4.

The ACF and the PACF of the residual shown in Figure 14 series has been used to check for the adequacy. Such plots indicated of no further inadequacies to be accounted for meaning that the residual series is a white noise.

The input model has been used to forecast future hourly input values upto 168-hour lead time. These forecasted hourly data along with the actual data are shown in Figure 15. These forecasts have been shown to have small errors upto 15-hour lead time, high errors for the next 48-hour lead time and much higher errors for the rest of the 168-hour lead time. One reason could be that the characteristic of the data used to build the input variable model which showed that there is a trend for an increase in the input variable future values. Such a growth did not happen but on the contrary the input variable future value has dropped for some other reason such wind speed that connot be explained by the historical input variable data. The other reason is the build up in the inaccuracies as a result of the serial correlation which means using forecasted values in issuing higher lead time forecasts.

2. The part that can be explained by the input variable (i.e., the TF model) has been built as follows. First, the input time series, $\nabla\nabla_{24}x(t)$, has been transformed into a white noise series, $\alpha(t)$, using the multiplicative seasonal autoregressive filter of equation (5.23). This process is called "prewhitening" the input [22]. The same transformation has also been applied to the stationary hourly load time series, $\nabla\nabla_{24}y(t)$, to obtain a transformed hourly load time series, $\beta(t)$ as:

$$\beta(t) = (1-\phi_1 B)$$
$$(1-\Phi^{24}B^{24}-\Phi_{48}B^{48}-\Phi_{72}B^{72}-\Phi_{96}B^{96}-\Phi_{120}B^{120}-\Phi_{144}B^{144}-\Phi_{168}B^{168}-\Phi_{192}B^{192})$$
$$\nabla\nabla_{24}y(t) \tag{5.24}$$

The above process of transformation makes the cross-correlation function (CCF) between the "prewhitened" hourly input series ,$\alpha(t)$, and the transformed hourly load series, $\beta(t)$,

Table 4. Estimates of the Summer Model Input Parameters

Parameter	Estimate	Approximate Standard Error	T-Ratio
ϕ_1	0.0942262	0.0405802	2.32
Φ_{24}	-0.7960220	0.0408917	-19.47
Φ_{48}	-0.5631500	0.0520753	-10.81
Φ_{72}	-0.3974720	0.0564689	-7.04
Φ_{96}	-0.2707100	0.0575077	-4.71
Φ_{120}	-0.3858680	0.0587925	-6.56
Φ_{144}	-0.2901780	0.0599997	-4.84
Φ_{168}	-0.2327650	0.0561597	-4.14
Φ_{192}	-0.1233760	0.0454162	-2.72

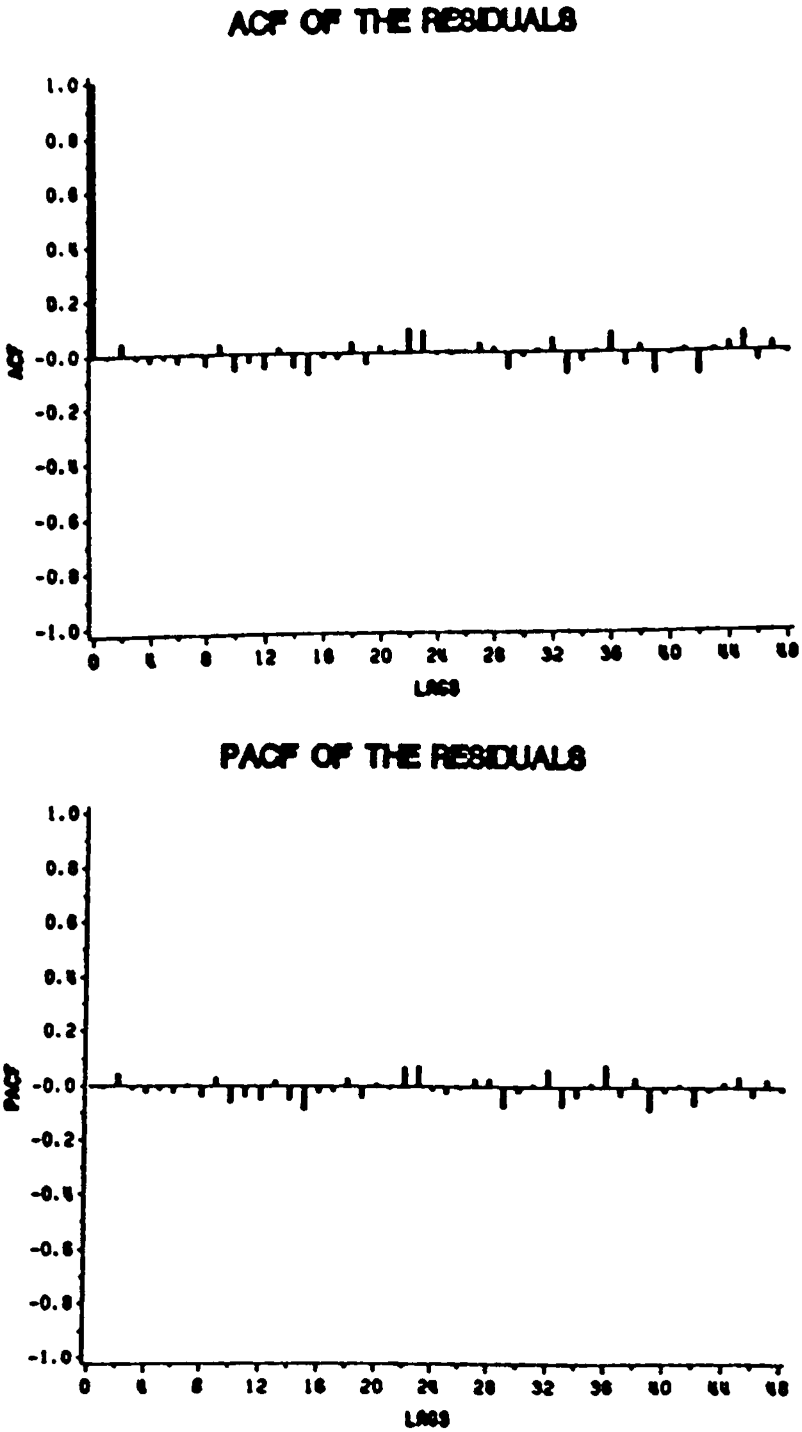
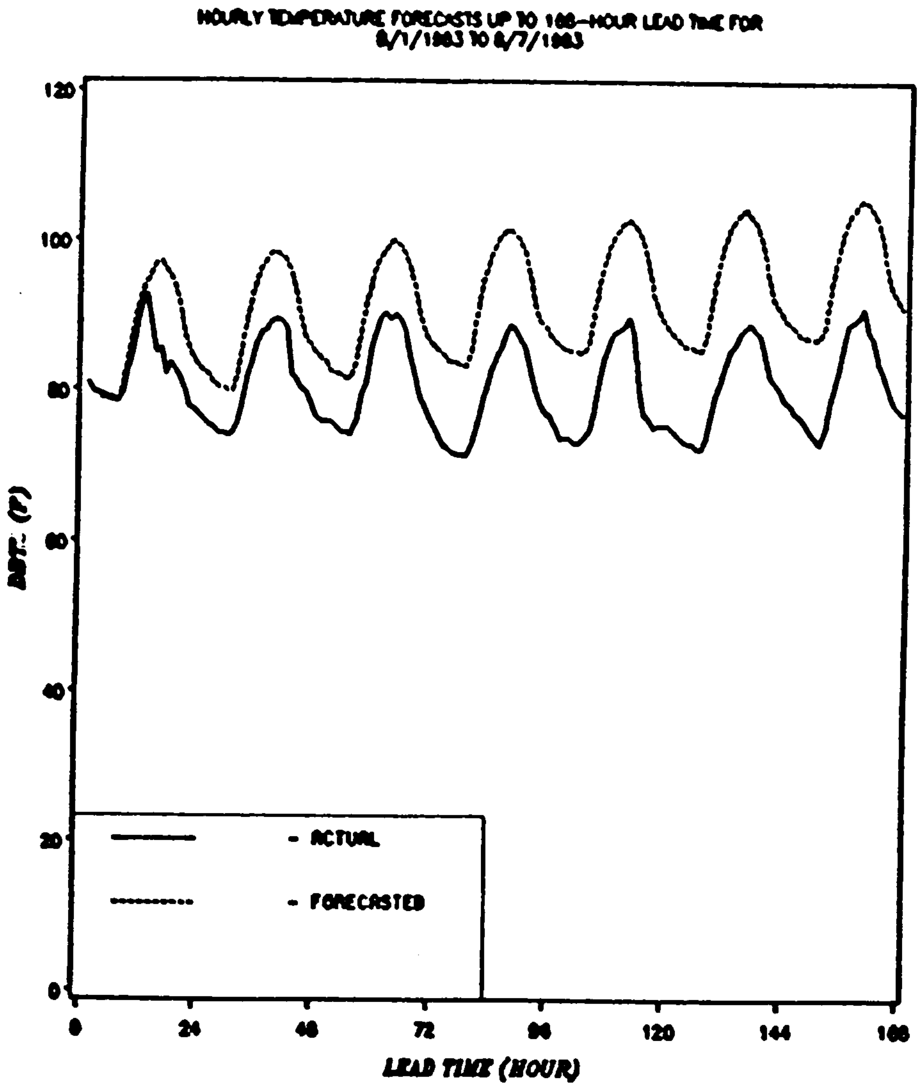


Figure 14. The Autocorrelation Function (ACF) and the Partial Correlation Function (PACF) of the noise series, $\alpha(t)$



MODEL:D(1,24)(1)(24,48,72,96,120,144,168,192))X=A

Figure 15. Actual and Forecasted Hourly Input (Dry Bulb Temperature) for 1-7 August 1983.

proportional to the impulse response function [22]. The (estimated) CCF between the input prewhitened),$\alpha(t)$, and the output (transformed), $\beta(t)$, has been obtained (using the four weeks of hourly input and load data)

as shown in Figure 16. The CCF plot indicated that there is no lag time response (i.e., b=0). The high impulse shown at lag time k=-1 can be understood as if the input is leading the output (i.e., noncausal system). This obviously is not the case and there is no obvious interpretation for this behavior. One interpretation could be due to the fact that an average hourly data from three areas has been used for the input variable which may have led to such a behavior. This possibility could be verified by considering the data from the three areas as three inputs.

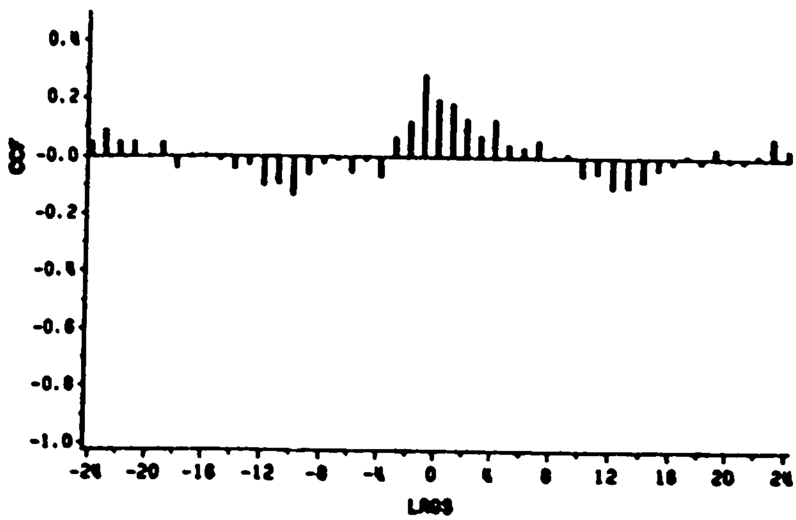
The orders s and r of the polynomials $\omega(t)$ and $\sigma(t)$ of the TF model have been identified from the CCF plot of Figure 16 as s = 2 and r = 0 to suggest a transfer function model as:

$$\nabla\nabla_{24}y(t) = (\omega_0 - \omega_1 B - \omega_2 B^2)\nabla\nabla_{24}x(t) \tag{5.25}$$

A preliminary estimate of the parameters of equation (5.25) can be found using the response impulse function (i.e., CCF values).

3. The noise series or the part that connot be explained by the effect of the input variable has been built as follows. First, the ACF and the PACF plots shown in Figure 17 have been used to identify the noise model. Second, the estimates of the parameters of both of the noise model and the TF model have been found using the conditional least-squares estimation technique as shown in Table 5. The estimate of the standard deviation of error has been found as 78.5 (MW).

   The model obtained has been checked using the ACF and the PACF of the residual series as shown in Figure 18. Such plots gave no indication of any further inadequacies to be accounted for.



MONTH: JULY 83 ;X=DBT−72
DATA BASE 7/5 TO 7/31/83

Figure 16. Crosscorelation Function (CCF) Between the "Prewhitened" Input and the Transformed Output , $\alpha(t)$ and $\beta(t)$

Table 5. Estimates of the Summer Hourly Load TF Model Parameters

Parameter	Estimate	Approximate Standard Error	T-Ratio
ω_0	11.009700	3.0491300	3.61
ω_1	-9.804660	3.0093600	-3.26
ω_2	-6.332720	3.0140300	-2.10
Θ_{168}	0.254892	0.0690987	3.69
ϕ_1	0.308202	0.0427860	7.20
ϕ_2	0.210072	0.0433921	4.84
ϕ_3	-0.101610	0.0417632	2.43
ϕ_{14}	-0.154745	0.0377323	4.10
Φ_{24}	-0.767134	0.0381804	-20.09
Φ_{25}	0.104670	0.0302246	3.46
Φ_{48}	-0.693132	0.0467932	-14.81
Φ_{72}	-0.660352	0.0517085	-12.77
Φ_{96}	-0.633507	0.0545685	-11.61
Φ_{120}	-0.700128	0.0555016	-12.61
Φ_{144}	-0.557970	0.0611952	-9.12

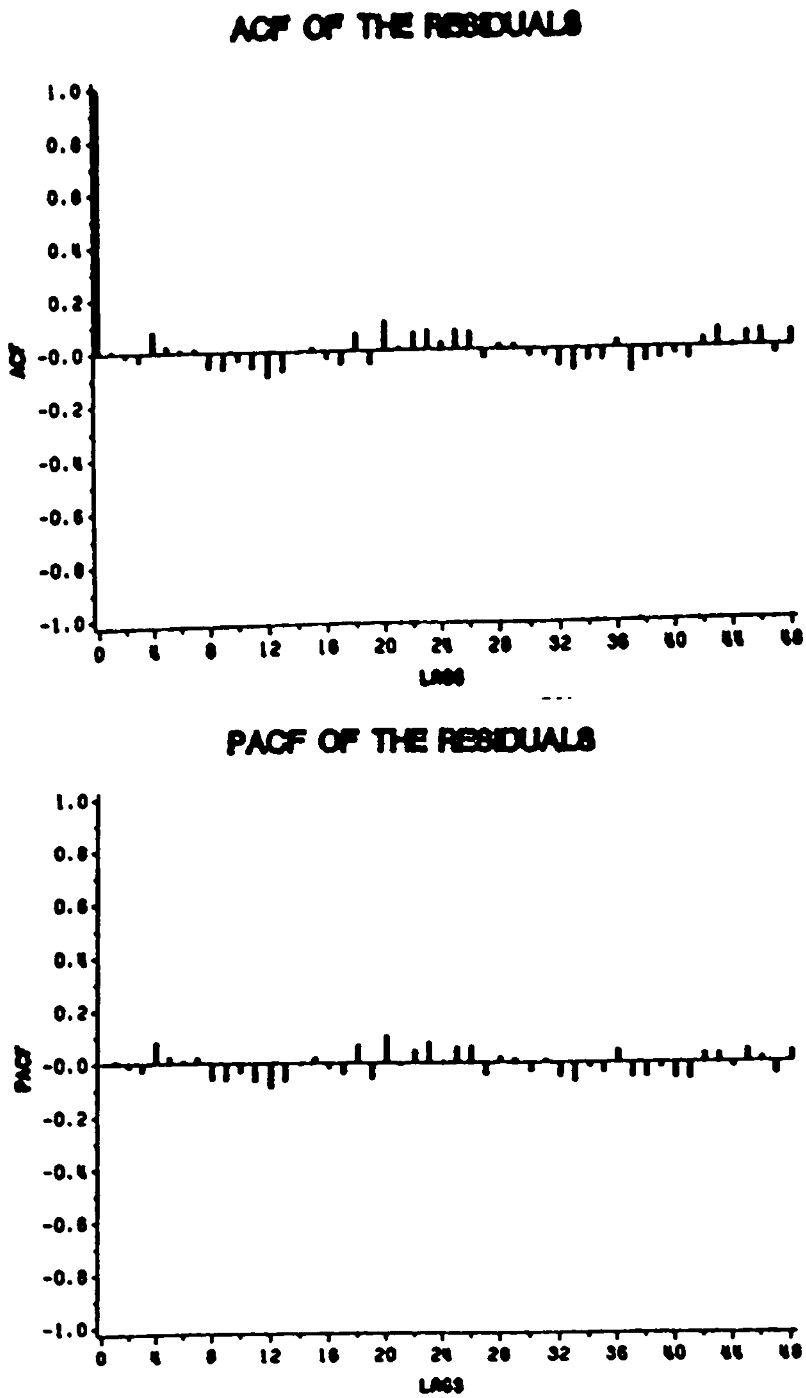
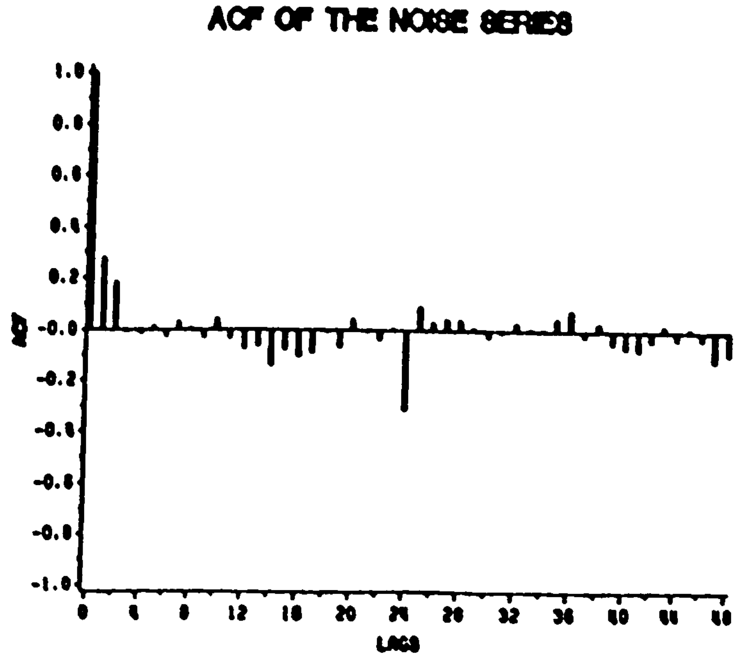


Figure 17. The Autocorrelation Function (ACF) and the Partial Correlation Function (PACF) of the noise series, n(t)



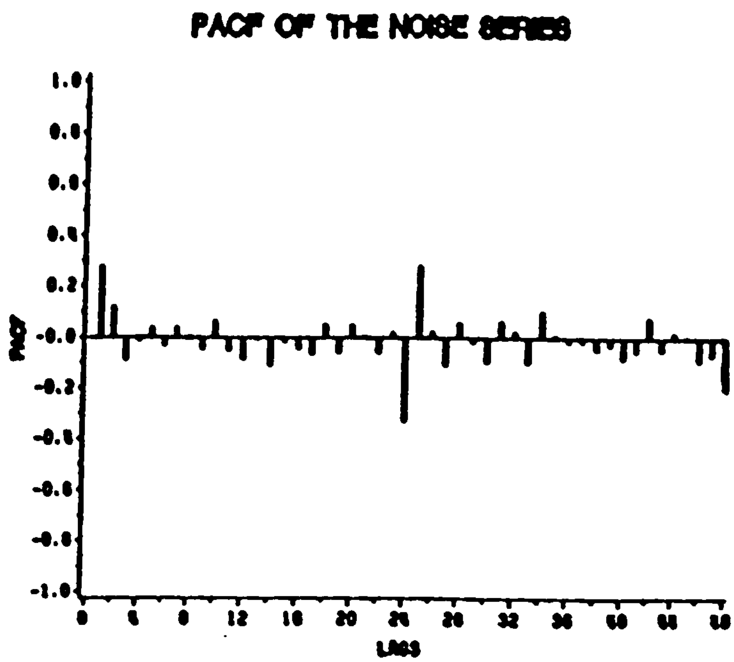


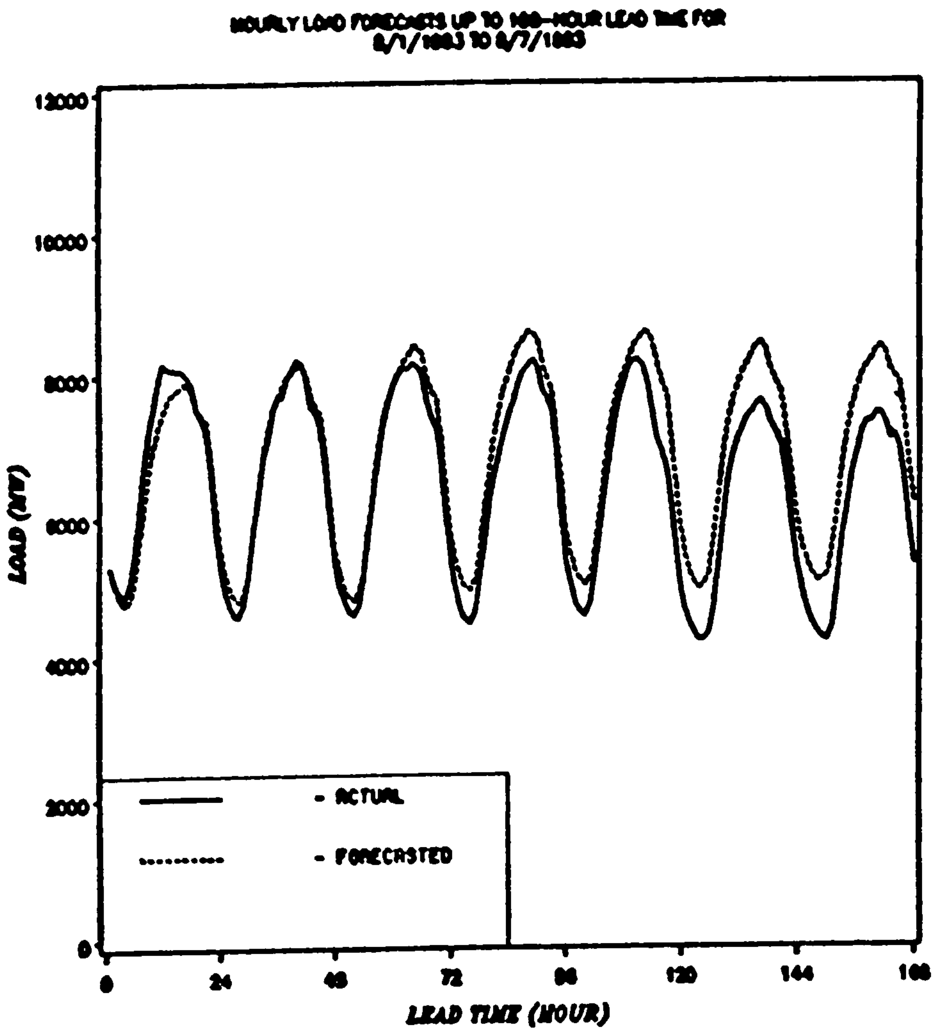
Figure 18. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Noise Series, a(t).

The complete TF model obtained has been used to issue a load forecast upto 168-hour lead time using both the forecasted hourly input values and the actual future hourly input values as given in Figures 19 and 20 respectively. The average absolute percent value of the error of the forecasts that have been based of forecasted dry bulb temperature has been found as 7.7 % with respect to the actual hourly load data and 5.7 % with respect to the weekly peak load. And the average absolute percent value of the error of the forecasts that are based of the actual future DBT data has been found as 4.2 % with respect to the hourly load data and 3.2 % with respect to the weekly peak load.

The accuracy of the TF model forecasts that have been issued using the forecasted input variable is less accurate than the univariate seasonal ARIMA model. This can be explained by the fact that the future input variable is not as predicted by the model obtained for the input series which resulted in contribution that has decreased the forecast accuracy. The actual future input variable when used in forecasting the hourly load upto 168-hour lead time has helped improving the accuracy of the forecast from 4.4 % when using the ARIMA model to 3.2 % in the TF model. This means that the accuracy of the forecasts has improved such that all the forecasts are contained with 10 % with respect to the weekly peak load. This also means that about 97 %, 93 %, and 88 % of the forecasts are within 8 %, 7 %, and 6 % average absolute error respectively with respect to the weekly peak load.

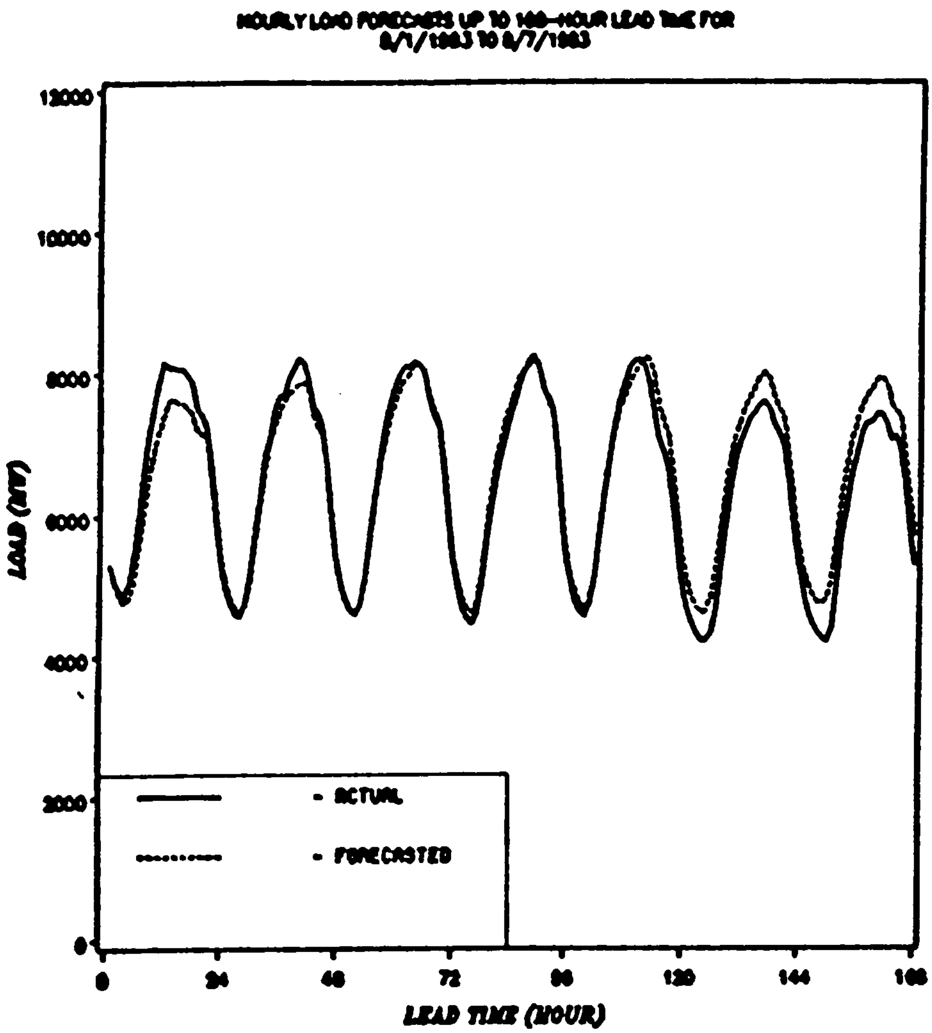
5.6 Results from Time Series Modeling

Results of applying the Box and Jenkins methodology to one-week load forecasts for all four seasons are presented in this section. These results have been obtained by building models similar to the models built for the Summer season given in the previous section (i.e., seasonal multiplicative ARIMA ad TF models). The exception to this is no TF model could be



MONTH:JULY 83 AND X=DBT−72
DATA BASE 7/5 TO 7/31/83
MODEL: D(1,24)Y=(1,2)D(1,24)X+((168)/((1,2,3,14)(24,25,48,72,96,120,144)))A2
WHERE D(1,24)(1)(24,48,72,96,120,144,168,192)X=A1

Figure 19. Actaul and Forecasted (TF model) Hourly Load Data for 1-7 August 1983 (Using Forecasted Input Data)



MONTH:JULY 83 AND X=DBT−72
DATA BASE 7/5 TO 7/31/83
MODEL: D(1,24)Y=(1,2)D(1,24)X+((168)/((1,2,3,14)(24,25,48,72,96,120,144)))A2
WHERE D(1,24)(1)(24,48,72,96,120,144,168,192)X=A1 (ACTUAL VALUES)

Figure 20. Actaul and Forecasted (TF model) Hourly Load Data for 1-7 August 1983 (Using Actual Input Data)

built for the Fall season as a result insignificant dependence between the load and the temperature in this season. The forecasts of these models upto 168-hour lead time in each season and the actual hourly load data are given in Figures 25 through 30 in appendix A. Summary of these forecasts are given in Table 6 (a) and (b) with respect to the hourly load data and the weekly peak load respectively.

5.7 Conclusion

This Chapter has covered the time series modeling approach for the hourly electric load. Detailed presentation for the model building using this method is demonstrated for the Summer hourly load model for both the seasonal ARIMA and the TF processes. Results have been presented using the models of the four seasons and have been summarized in a tubular form. Such results are needed for comparison with the knowledge-based expert system approach that will be presented next.

Table 6. Average Absolute Percent Forecast Error for Four Seasons

(a) With Respect to the Hourly Load Data

Season	ARIMA Model	TF Model	
		Forcasted Input	Actual Input
Summer	6.0 %	7.7 %	4.2 %
Fall	3.8 %	n/a	n/a
Winter	5.4 %	3.6 %	4.3 %
Spring	7.2 %	5.6 %	n/a

(b) With Respect to the Weekly Peak Load

Season	ARIMA Model	TF Model	
		Forcasted Input	Actual Input
Summer	4.4 %	5.7 %	3.2 %
Fall	3.1 %	n/a	n/a
Winter	4.3 %	2.9 %	3.5 %
Spring	5.4 %	4.3 %	n/a

Chapter VI

EXPERT SYSTEMS APPROACH TO LOAD FORECASTING

6.1 Introduction

A different approach to the load forecasting problem will be addressed in this chapter. This approach is based on applying expert system techniques to the load forecasting problem. Such techniques were first applied by Rahman and Bhatnagar to short-term load forecasting [2,4]. Rahman and Bhatnagar have developed two algorithms. One algorithm generates forecasts upto 6-hour lead time and the other generates forecasts upto 24-hour lead time. Lately, Rahman and Baba extended the work on the 24-hour lead-time load forecast. They developed an improved 24-hour load forecasting algorithm for demand-side management application [83,84]. The maximum lead-time used in was 24 hours. For higher lead-time forecast, another rule-based algorithm has been reported in the literature. This algorithm is called ALFA (Automatic Load Forecasting Assistant) [3]. ALFA is capable of generating forecasts upto 48-hour lead-time. However, this algorithm requires a huge data base. This data base consists of eleven variables and has a depth of 10 years of hourly data for these variables. ALFA runs on a high powered mainframe computers namely IBM-3090.

Therefore, the focus of this chapter is the applicability of rule-based expert systems to load forecasting in higher lead times, but reduced computational burden. Specifically this work is aimed at developing a 168-hour (1-week) lead time load forecasting technique using a knowledge-based approach. This is done in the form of rules in a rule-base. The rules used in this work are extracted from the statistical relationships between load and weather variables, other historical observations and perceptions of domain experts. The rule-base is developed using these relationships that govern the impact of weather conditions and other physical forces on the prevailing load shapes. The accuracy of the forecast using this program is at least as good as those of statistical technique. Because of its simple features, this technique is suitable for implementation on microcomputers.

Rule-base techniques are the means by which most current expert systems are described. An explanation for rule-based (expert system) load forecasting is provided in Section 6.2. Next, in Section 6.3 the one-week lead-time load forecast (rule-based) program is discussed. This includes explanation of the data base requirement, the selection of the data points needed for issuing the load forecast, and the load forecast calculations. Results and discussion using this technique is covered in Section 6.4. A conclusion about this work is presented in Section 6.5.

6.2 Rule-Based Load Forecasting

Expert systems are new techniques that have emerged as a result of advances in the field of artificial intelligence (AI) in the last two decades. These systems use a knowledge-based approach in solving problems in a specific problem area. This means an extensive body of knowledge about the problem domain is needed. This body of knowledge has to be formalized as a collection of rules and facts in order for the system to establish conclusions about the problems involved from this given knowledge.

A discussion of expert systems and their applications was presented in chapter 4. In brief, an expert system is a computer program (though not algorithmic) which has the ability to act as an expert. This means this program can reason, explain, and have its knowledge base expanded as new information becomes available to it.

The load forecast model (in the expert system technique) is built using the knowledge about the load forecast domain from an expert in the field. The "Knowledge Engineer" extracts this knowledge from load forecast (domain) expert by what is called the acquisition module component of the expert system. This knowledge is represented as facts and rules by using the first predicate logic to represent the facts and IF-THEN production rules. This representation is built in what is called the knowledge base component of the expert system. The search for solution or reasoning about the conclusion drawn by the expert system is performed by what is known as the "Inference Engine" component of the expert system. For any expert system it has to have the capability to trace its reasoning if asked by the user. This facility is built through an explanatory interface component.

Most current expert systems are described using rule-based techniques. The rule-base represents the set of rules that governs the behavior of the system. These rules are usually called production rules. The basic form for representing these rules is the IF-THEN production rules. This means for the actions under the THEN statement to be appropriate all the conditions under the IF statement must be true.

The rules in the data base can be represented either in the problem-oriented languages such as FORTRAN and PASCAL or symbol-oriented languages such as LISP and PROLOG. Usually the symbol-oriented languages (known as rule-base languages) are suitable for large data bases where there are numerous rules which need to be represented in the data base. Besides, the symbol-oriented languages are more open in the sense that new rules can be added easily.

The rule-based program of this work has been developed in FORTRAN language. This is due to the fact that the number of rules are not that large until now. However, the symbol-oriented languages could also be used for the development of this rule-base load forecasting algorithm.

6.3 Forecast Program

This program is a 168-hour lead-time electric load demand predictor. This program uses a rule (or knowledge) base in the representation of the load forecast model. This knowledge base comprises the rules and relationships that are used in building the load forecast model. The rules may include the following:

- Rules for identifying the variables that are necessary in developing the load forecast model.
- Rules for identifying the the relationships that will be used in the calculation of the load predictions; and
- Rules for enabling the program to adapt to the different variations in weather conditions.

The rules and the relationships that were used in developing the load forecast model are based on: (1) the long term statistical relationships and (2) the knowledge and the experience of the system operator in the electric utility industry. In spite of the fact that the knowledge base consists of few rules, the forecasts generated are quite satisfactory when compared to the ones generated using conventional statistical techniques.

6.3.1 Data base

The data base requirement for this algorithm consists of four weeks of hourly historical load and weather information plus one week of hourly future weather information. Each record in this data base consists of the following:

1. Hourly historical MW load demand data.

2. Hourly historical and future weather data.

3. Year, month, day, hour, and day type data that associate with the load and/or weather data.

The weather data consists of dew point temperature, wind speed, dry bulb temperature, wet bulb temperature and relative humidity. All of these variables however are not essential for all hours. In fact some of them will be used only in a specific season while in other seasons they will not. Furthermore, some of them will be valuable in particular circumstances in a given season. The reason behind using a universal data base is explained by the features implemented in the load forecasting algorithm. Since this algorithm will be developed using rule-based techniques, it will be able to select the required variables for the prediction process in any specific season or circumstance.

6.3.2 Selection of data for forecasting

The selection of data for forecasting is based on weekly and seasonal variations. The weekly seasonalities dictate that similar day types have similar load shapes. This helps the construction of the one-week lead time load forecasts from current and previous days grouped on the basis of day types. The seasonal variations dictate that changes in the load shape of similar day types become apparent for higher separation in lag time. This means older day type data are less useful in producing accurate forecasts. Also, it must be noted here that the forecast interval is always seven days.

Three sets of historical data points from the same day type were found to be the best for producing the load forecast at the current stage. If one of the historical days happens to be a holiday, then data set from the previous similar day is used to replace the data set of this day. In addition to the selected historical data points a set of future weather data about the forecasted day is needed. The criterion for considering three historical sets of data points as the best selection was based on the average of absolute error of the forecasts.

Each set of the historical data consists of load and weather information at the same hours on the selected historical day and the forecast day. Each set also includes information about average weather information at some prespecified lag time. The future data consists of similar weather information at the forecasted hour plus average weather information at the same prespecified lag time with the historical data. The selected weather variables do not include all the variables in the data base. This is obvious since each season has it own weather variables which play a role for the demand for electricity.

6.3.3 Load forecast calculation

The load forecast will be calculated using a multiplicative load forecast model at its current state. This model consists of a "base load forecast" and multiplicative correction factors. In some circumstances additive corrections are needed to rectify the load forecast. The model for predicting a 168-hour lead-time load for summer is written for the i^{th} hour (seven-days ahead) in the form:

YFCST(i) = BASEMW(i)*FACTR1(i)*FACTR2(i)*FACTR3(i)

+ DMWBTH(i)*(THIF(i)-BASTHI(i))

+ DMWBDB(i)*(DBTF(i)-BASDBT(i)) (6.1)

where,

BASEMW(i)	=	forecasted base MW load
FACTR1(i)	=	factor accounting for load growth
FACTR2(i)	=	factor accounting for weather differences effect
FACTR3(i)	=	factor accounting for weather inertia differences effect
DMWBTH(i)	=	factor rectifying the account for large differences in THI
DMWBDB(i)	=	factor rectifying the account for large differences in DBT
THIF(i)	=	temperature-humidity index (THI) at the hour of forecasted load
BASTHI(i)	=	equivalent THI associated with the base MW load
DBTF(i)	=	dry bulb temperature (DBT) at the hour of forecasted load
BASDBT(i)	=	equivalent DBT associated with the base MW load

The differences mentioned above is meant between the weather conditions associated with the selected data points for producing the forecast, and the weather conditions associated with the required load forecast.

The parameters in the above load-forecast equation are calculated as follows:

- The "reference load" MW load, BASEMW(i), is calculated by simply averaging the MW loads in the i^{th} hours in the selected day types, n, as:

$$BASEMW(i) = \sum_{j=1}^{j=n} \frac{1}{n} MW(i,j) \tag{6.2}$$

where n is the number of selected historical day types.

- In a similar fashion, the equivalent THI and DBT for the "reference load" MW is calculated by simply averaging the respective values of THI and DBT in i^{th} hour in the selected day types, n, as:

$$BASTHI(i) = \sum_{j=1}^{j=n} \frac{1}{n} THI(i,j) \tag{6.3}$$

$$BASDBT(i) = \sum_{j=1}^{j=n} \frac{1}{n} DBT(i,j) \tag{6.4}$$

- The correction factor FACTR1(i) is introduced to account for the load growth. The expression for this factor has not been settled to a specific rule. A deeper understanding of the system load growth helps achieving accurate higher lead-time forecasting. For the moment, the growth is considered zero, and therefore FACTRI(i) = 1.0.

- The correction factor FACTR2(i) accounts for the differences between the weather conditions at the hour of forecasted load and the hour of the selected historical data points. This factor is expressed as:

$$\begin{aligned} FACTR2(i) &= \frac{THIF(i)}{BASTHI(i)} \qquad DBT > 80.0\,F^{o} \\ &= \frac{DBTF(i)}{BASDBT(i)} \qquad DBT \leq 80.0\,F^{o} \end{aligned} \tag{6.5}$$

- The correction factor FACTR3(i) accounts for the difference in the effect of the "inertia" generated as a result of lag time weather effect on the selected historical load data points and the effect of the "inertia" that would be generated as a result of lag time weather effect on the forecast load. This factor has an expression written in the form:

$$FACTR3(i) = \frac{AVBTHF}{AVGTHW} \qquad DBT > 80.0F^{o}$$
$$= \frac{AVGDBF}{AVGDBW} \qquad DBT \leq 80.0F^{o} \tag{6.6}$$

where,

$$AVGTHF = \sum_{k=1}^{k=L} \frac{1}{L} THIF(i-k) \tag{6.7}$$

$$AVGDBF = \sum_{k=1}^{k=L} \frac{1}{L} DBTF(i-k) \tag{6.8}$$

$$AVGTHW = \sum_{j=1}^{j=n} \frac{1}{n} \sum_{k=1}^{k=L} \frac{1}{L} THI(i-k,j) \tag{6.9}$$

$$AVGDBW = \sum_{j=1}^{j=n} \frac{1}{n} \sum_{k=1}^{k=L} \frac{1}{L} DBT(i-k,j) \tag{6.10}$$

and where,

L	=	considered lag time hours for accounted weather conditions
THIF(i)	=	THI at the i^{th} hour in the forecasted day
DBTF(i)	=	DBT at the i^{th} hour in the forecasted day
THI(i,j)	=	THI at the i^{th} hour in the selected j^{th} day type
DBT(i,j)	=	DBT at the i^{th} hour in the selected j^{th} day type

The correction factors DMWBTH and DMWBDB were introduced to account for large differences between the forecasted and the selected day weather conditions. These factors will help improving the forecasts in days where the multiplicative model forecasts are in need of rectification due to the sharp increase or decrease in weather conditions in the forecasted day as compared to the weather conditions in the selected historical day types. Analysis of long term historical data and interviews with the electric utility experts resulted in the values shown in Table 7 for both of these factors. The values shown in Table 7 are in MW/°F. These values are applied where saturation has not reached. The saturation in the effect of these factor has been suggested as 10 °F difference in effective temperature between the "reference load" and the forecasted load.

6.4 Results and Discussions

The rule-based program in its current state has a small data base. This data base comprises rules that enable issuing a 168-hour load forecast in the summer season. Although more rules are needed for the summer forecasts, the results using the current data base and the set of rules look promising. The algorithm has been tested in issuing one-week ahead hourly and daily peak load forecast for the month of August 1983. This test has been performed using hourly load for a southeastern utility and average weather information about their service area. The analysis of the error of the 168-hour lead time forecast are presented in Table 8 through Table 13 and Figures 21 through 24. For the 7-day lead time daily peak load forecast, the results are presented in Table 14 and Figure 25. These presented results are discussed as follows:

6.4.1 The 168-hour lead time hourly load prediction

Table 8 and Table 9 present the average of the one-week lead-time absolute hourly load forest percent error using different lag time temperature effect for evaluating FACTR3(i). Table

Table 7. Addative Correction Factors Coefficients for the Summer Model

Parameter	Day Interval				
	12-4AM	5-9AM	10AM-1PM	2-7PM	8-11PM
DMWBTH	10	15	20	40	20
DMWBDB	0	0	20	40	20

8 presents the forecast percent error with respect to hourly load data while Table 9 presents the forecast percent error with respect to daily peak load data. Table 8 and Table 9 also present an average for the different issued forecasts for the the whole tested period. Table 10 and Table 11 present statistical analysis results of the one-week load forecast error to the whole period for the different issued forecasts. Table 10 presents these results where the forecast errors are calculated with respect to the hourly load as in Table 10 (a) and to the daily peak load as in Table 10 (b). Table 11 presents these statistical analysis results for the MW load forecast error. The results shown in Table 8 through Table 11 indicate that the minimum average value for the absolute error is achieved when considering 20-hour lag time for the effect weather conditions. However, the difference when considering 16 and 24 hours lag time are still close to that of the 20-hour lag time weather effect. Different rules could be constructed for selecting the length of the lag time needed if it is found that this lag time is a function of the weather variables and/or a function of the time of the day. Table 12 and Table 13 present the cumulative distribution of the absolute percent forecast errors in the range less than 5 % and the range 5 % to less than 8 % for the best four lag time temperature effect . Details of distribution and cumulative distributions of the absolute percent load forecast error are shown in Table 36 through Table 43 in Appendix B. These distributions also indicate that not much can be gained by varying the depth of the lag time beyond lag time of 16 hours. These tables together indicate that large error are occurring in special days or cluster of days. Part of this can be explained by the fact that week-ends usually have large percent error as regarding the load level in these days and their fluctuations. In other days such as the thirteenth through the sixteenth it is found that the temperature dropped suddenly due to a cold wave. This resulted in the shut down of many air-conditioning equipment and accordingly a large drop in the load level. Therefore, the relationship governing the load forecast in these days are not exactly as developed in the algorithm. These relationships need to be reexamined and modified. The current rules for DMWBTH(i) and DMWBDB(i) factors that were used have improved the accuracy of the prediction to some degree. More understanding and knowledge can produce more rules to further rectify the forecast in such circumstances.

Table 8. One-Week Lead Time Absolute Load Forecast Percent Error (w.r.t. Hourly Load) for Different Lag Time Temperature Effect

day	type	1 hour (%)	4 hours (%)	8 hours (%)	12 hours (%)	16 hours (%)	20 hours (%)	24 hours (%)
1	1	3.12	2.98	2.75	2.24	1.88	1.87	2.09
2	2	2.89	2.74	2.70	2.73	2.62	2.38	2.09
3	3	1.84	1.68	1.35	1.31	1.35	1.39	1.36
4	4	2.16	2.11	2.19	2.18	2.07	1.90	1.73
5	5	2.44	1.83	1.33	1.57	1.85	2.15	2.32
6	6	2.82	2.60	2.13	1.83	2.08	2.30	2.37
7	7	3.21	3.25	3.08	2.84	2.63	2.45	2.41
8	1	1.72	1.96	2.39	2.82	3.17	3.42	3.58
9	2	2.52	2.29	2.12	2.12	2.17	2.26	2.45
10	3	3.83	3.68	3.51	3.15	2.73	2.30	1.88
11	4	2.91	2.58	1.83	1.42	1.38	1.49	1.54
12	5	2.56	2.46	2.59	2.53	2.33	2.36	2.72
13	6	6.67	5.98	4.92	3.67	2.70	2.02	1.92
14	7	3.72	3.80	3.92	4.13	4.28	4.18	3.77
15	1	8.68	8.63	7.75	6.76	5.87	5.39	5.37
16	2	5.77	5.45	4.76	4.15	3.67	3.70	3.80
17	3	4.79	4.42	3.96	3.41	2.79	2.45	2.27
18	4	5.37	5.04	4.68	4.53	4.45	4.29	3.97
19	5	4.35	4.23	4.04	3.62	3.10	2.84	2.98
20	6	2.97	2.67	2.41	2.16	2.59	2.98	3.17
21	7	8.71	8.06	7.22	6.38	5.54	4.93	4.63
22	1	3.14	2.90	2.29	2.24	2.62	2.92	2.99
23	2	4.70	3.99	3.25	2.24	1.68	1.72	1.99
24	3	2.96	2.46	1.67	1.53	1.73	2.11	2.25
25	4	3.02	2.81	2.57	2.42	2.51	2.52	2.50
26	5	3.10	3.07	2.47	2.03	2.01	2.13	2.12
27	6	3.25	2.66	2.06	1.70	1.65	1.63	1.52
28	7	4.73	4.05	3.26	3.25	3.29	3.28	3.10
29	1	3.53	3.47	3.48	3.35	3.33	3.46	3.49
30	2	3.22	3.15	3.32	3.36	3.43	3.61	3.90
31	3	1.76	1.55	1.41	1.42	1.46	1.48	1.54
Av.		3.76	3.50	3.14	2.87	2.74	2.71	2.70

Table 9. One-Week Lead Time Absolute Load Forecast Percent Error (w.r.t. Daily Peak) for Different Lag Time Temperature Effect

day	type	1 hour (%)	4 hours (%)	8 hours (%)	12 hours (%)	16 hours (%)	20 hours (%)	24 hours (%)
1	1	2.76	2.57	2.29	1.84	1.52	1.50	1.65
2	2	2.40	2.25	2.17	2.16	2.08	1.95	1.75
3	3	1.50	1.37	1.06	1.03	1.07	1.11	1.09
4	4	1.75	1.71	1.79	1.80	1.74	1.64	1.51
5	5	1.98	1.51	1.08	1.25	1.45	1.68	1.82
6	6	2.21	2.07	1.77	1.55	1.69	1.85	1.89
7	7	2.87	2.88	2.72	2.52	2.34	2.19	2.14
8	1	1.39	1.61	1.99	2.37	2.69	2.94	3.09
9	2	2.06	1.88	1.76	1.77	1.79	1.84	1.96
10	3	3.21	3.14	3.05	2.78	2.44	2.06	1.68
11	4	2.15	1.93	1.43	1.20	1.18	1.24	1.25
12	5	2.05	1.93	2.08	2.09	1.97	2.00	2.34
13	6	6.20	5.54	4.49	3.30	2.39	1.79	1.69
14	7	2.95	3.05	3.17	3.30	3.42	3.36	3.05
15	1	7.23	7.21	6.45	5.54	4.73	4.30	4.26
16	2	5.02	4.72	4.09	3.52	3.10	3.12	3.21
17	3	4.19	3.87	3.42	2.88	2.34	2.05	1.91
18	4	4.46	4.16	3.86	3.76	3.73	3.65	3.43
19	5	3.29	3.22	3.10	2.81	2.46	2.31	2.47
20	6	2.16	1.90	1.71	1.53	1.94	2.28	2.46
21	7	7.33	6.82	6.16	5.45	4.72	4.16	3.82
22	1	2.60	2.26	1.68	1.66	1.99	2.30	2.44
23	2	4.14	3.53	2.82	1.92	1.40	1.35	1.50
24	3	2.70	2.22	1.51	1.27	1.36	1.69	1.84
25	4	2.56	2.37	2.15	2.02	2.07	2.03	1.96
26	5	2.44	2.42	1.88	1.48	1.46	1.57	1.56
27	6	2.52	2.06	1.54	1.19	1.20	1.28	1.28
28	7	3.76	3.19	2.55	2.52	2.54	2.55	2.44
29	1	2.44	2.40	2.55	2.59	2.58	2.65	2.65
30	2	2.41	2.40	2.57	2.63	2.69	2.79	2.97
31	3	1.44	1.26	1.14	1.15	1.18	1.20	1.24
Av.		3.10	2.87	2.58	2.35	2.24	2.21	2.20

Table 10. One-Week Lead Time Percent Forecast Error Statistics for August 1983 for Different Lag Time Temperature Effect

(a) with respect to hourly load

lag time (hours)	forecast error average	forecast error st. dev.	forecast error |max value|
1	3.76	3.14	20.48
4	3.50	2.81	19.17
8	3.14	2.50	18.77
12	2.83	2.27	17.86
16	2.74	2.14	17.50
20	2.71	2.11	17.04
24	2.70	2.14	16.62

(b) with respect to daily peak load

lag time (hours)	forecast error average	forecast error st. dev.	forecast error |max value|
1	3.10	2.81	16.85
4	2.89	2.52	14.18
8	2.58	2.20	13.38
12	2.35	1.97	12.72
16	2.24	1.81	12.27
20	2.21	1.76	12.02
24	2.20	1.76	11.60

Table 11. One-Week Lead Time Absolute Hourly MW Forecast Error Statistics for Different Lag Time Temperature Effect

lag time (hours)	forecast error average	forecast error st. dev.	forecast error |max value|
1	227.42	191.37	975.71*
4	211.26	169.56	885.00
8	189.10	148.42	850.71
12	173.12	135.87	736.86
16	165.87	127.68	710.86
20	164.95	126.12	696.19
24	165.44	128.24	673.65

* these statistics are expressed in % w.r.t. hourly and daily peak load in Table 10

Table 12. One-Week Lead Time Absolute Load Forecast Percent Error (w.r.t. Hourly Load) for Different Lag Time Temperature Effect

day	12 hours		16 hours		20 hours		24 hours	
	$0 \leq \% < 5$	$5 \leq \% < 8$	$0 \leq \% < 5$	$5 \leq \% < 8$	$0 \leq \% < 5$	$5 \leq \% < 8$	$0 \leq \% < 5$	$5 \leq \% < 8$
1	96	4	96	4	100	0	92	8
2	96	4	96	4	96	4	96	4
3	100	0	100	0	100	0	100	0
4	100	0	100	0	100	0	100	0
5	96	4	100	0	100	0	100	0
6	100	0	100	0	96	4	96	4
7	79	21	79	21	88	12	88	12
8	92	8	83	17	83	17	83	17
9	100	0	96	4	96	4	96	4
10	88	12	88	12	96	4	96	4
11	96	4	96	4	96	4	100	0
12	100	0	96	4	92	8	88	12
13	79	17	92	8	96	4	96	4
14	71	13	63	21	67	17	67	17
15	38	25	41	33	67	8	67	12
16	67	17	75	25	67	29	67	29
17	79	21	96	4	100	0	100	0
18	67	29	75	21	75	21	79	17
19	83	17	96	4	96	4	96	4
20	100	0	96	4	100	0	92	8
21	25	58	41	50	58	33	67	21
22	100	0	88	12	83	17	79	21
23	100	0	100	0	92	8	88	12
24	100	0	100	0	100	0	96	4
25	88	13	92	8	92	8	88	12
26	92	4	96	4	92	4	92	4
27	100	0	100	0	100	0	100	0
28	83	17	83	17	79	21	83	17
29	92	8	92	8	79	17	75	21
30	63	37	63	37	63	37	63	29
31	96	4	96	4	96	4	96	4
AV.	87.9	9.7	88.5	9.4	87.9	9.7	87.9	9.7

Table 13. One-Week Lead Time Absolute Load Forecast Percent Error (w.r.t. Daily Peak) for Different Lag Time Temperature Effect

day	12 hours		16 hours		20 hours		24 hours	
	$0 \le \% < 5$	$5 \le \% < 8$	$0 \le \% < 5$	$5 \le \% < 8$	$0 \le \% < 5$	$5 \le \% < 8$	$0 \le \% < 5$	$5 \le \% < 8$
1	96	4	100	0	100	0	96	4
2	96	4	100	0	100	0	100	4
3	100	0	100	0	100	0	100	0
4	100	0	100	0	100	0	100	0
5	100	0	100	0	100	0	100	0
6	100	0	100	0	96	4	100	0
7	79	21	79	21	88	12	88	12
8	92	8	92	8	92	8	83	17
9	100	0	100	4	100	0	100	4
10	88	12	88	12	96	4	100	4
11	96	4	96	4	96	4	100	0
12	100	0	100	0	100	0	100	0
13	79	17	92	8	96	4	96	4
14	79	17	83	8	75	12	75	21
15	46	29	54	29	75	8	75	8
16	67	33	75	25	67	33	67	33
17	88	12	96	4	100	0	100	0
18	88	12	83	12	83	13	83	12
19	92	8	96	4	100	0	100	0
20	100	0	100	0	100	0	100	0
21	42	42	58	33	63	37	75	25
22	100	0	96	4	92	8	88	12
23	100	0	100	0	100	0	100	0
24	100	0	100	0	100	0	100	0
25	92	8	96	4	96	4	96	4
26	96	4	96	4	96	4	96	4
27	100	0	100	0	100	0	100	0
28	100	0	96	4	96	4	92	8
29	100	0	100	0	96	4	96	4
30	83	17	83	17	83	17	83	17
31	96	4	96	4	96	4	96	4
AV.	89.9	8.4	92.1	6.7	92.6	6.3	93.0	6.2

These results indicate that the percent forecast error is about 2.2% (with respect to daily peak). This result is quite satisfactory as compared to the same forecasts that can be produced using statistical (conventional) techniques. The distribution of these errors indicates that the confidence that the error will not exceed 8.0% is more than 97.6% (20-hour lag time weather effect) with respect to the hourly load as shown in Table 12. This could rise to more than 98.9% when considering the confidence with respect to the daily peak load as shown in Table 13. The actual and forecasted load using 20-hour lag time effect that gives the minimum average MW error for the whole period is shown in Figures 21 through Figure 24.

6.4.2 The 7-day lead-time daily peak prediction

The 7-day ahead daily load prediction was calculated using the same rules and formulas that have been applied to the hourly load forecast as presented and discussed in previous sections. The highest such hourly load was then picked up as the peak load of the day. The forecast error statistics of the daily peak load is shown in Table 14. The results also indicate that the best lag time effect for the temperature in constructing FACTR3(i) is 20 hours. They also indicate that average absolute of the daily peak load error is about 216 MW with standard deviation of about 123 MW and maximum error of 549 MW. The actual and predicted daily peak load for the whole month of August 83 using 20-hour lag time temperature effect is shown in Figure 25.

6.5 Conclusion

In this chapter an expert system approach has been applied to the one-week lead-time load forecast problem. Though few rules and relationships are used in this work, results obtained are encouraging as compared to results that could be obtained using conventional

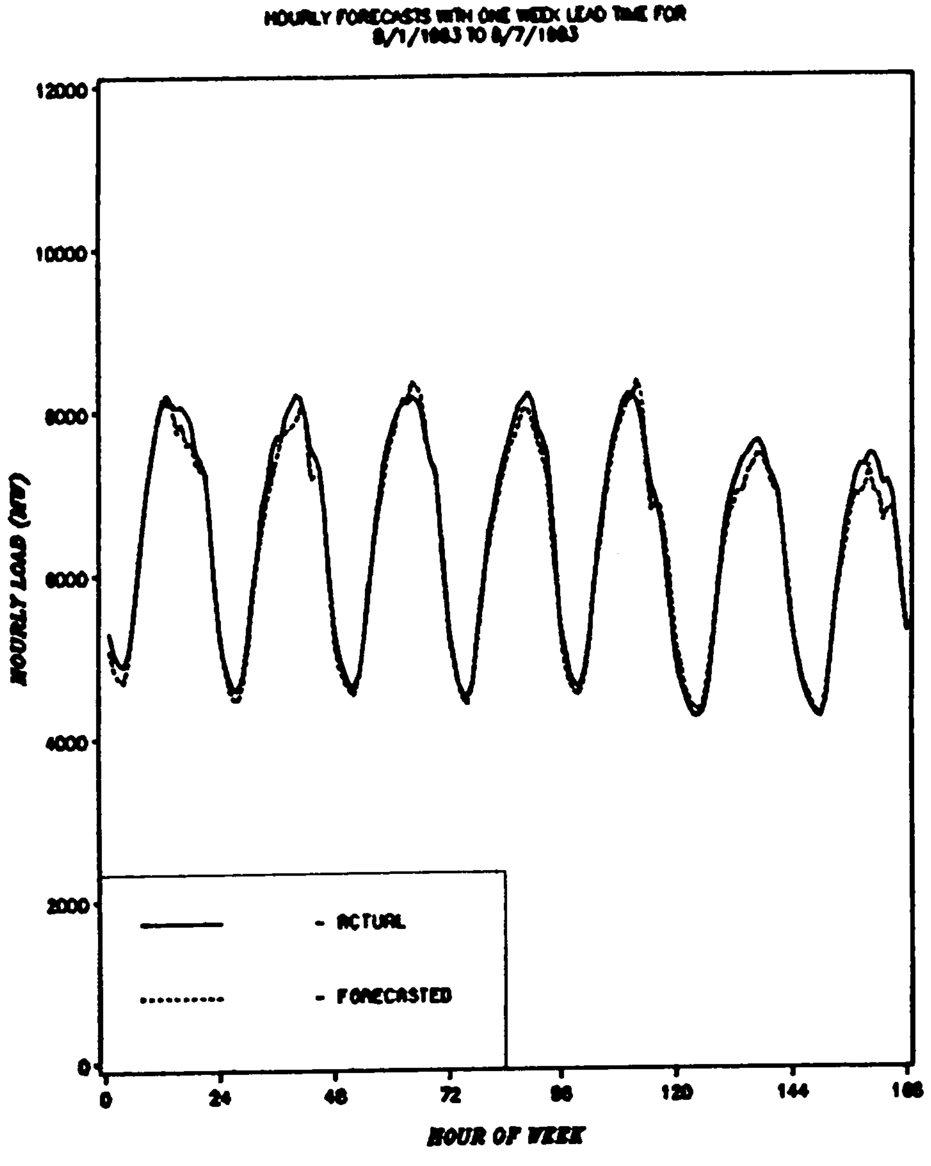


Figure 21. Actaul and Forecasted Summer Load (1-7 August 1983) Using 20-hour Lag Time Effect for Temperature Variable

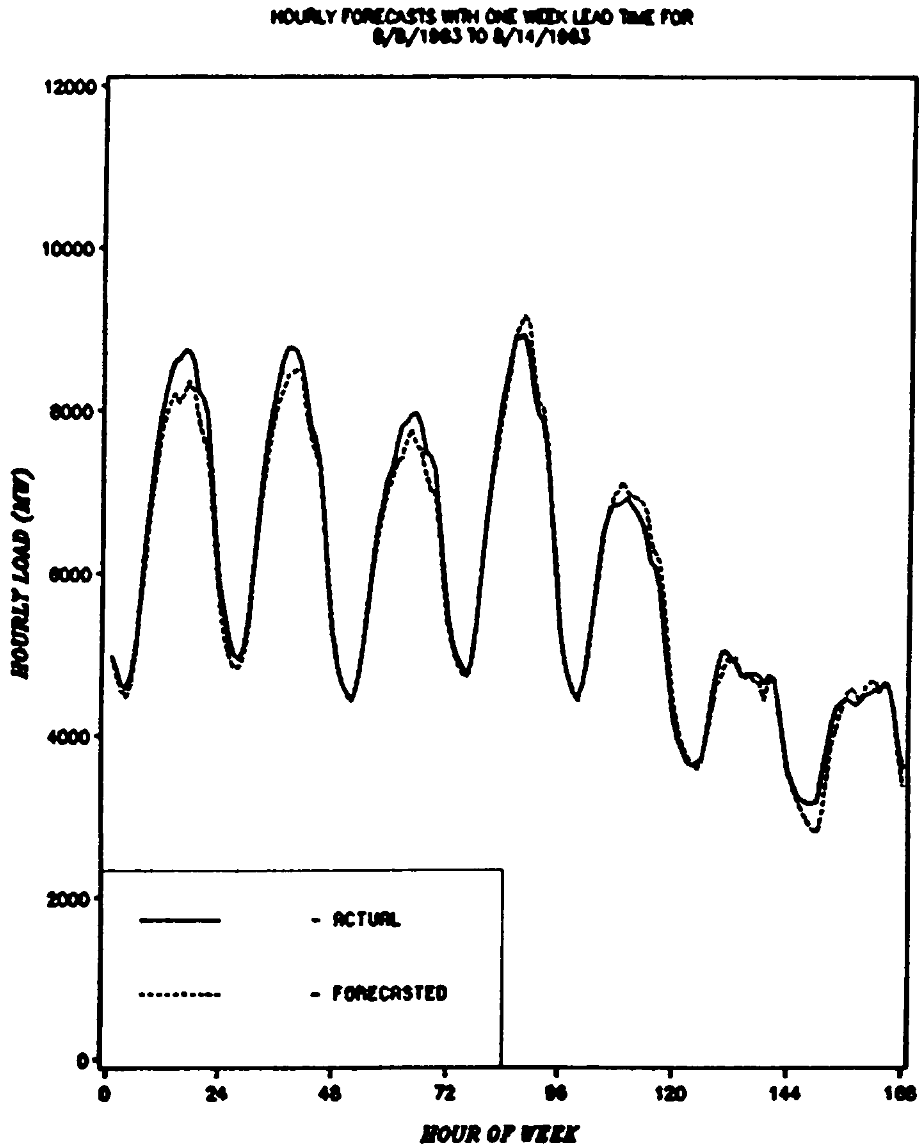


Figure 22. Actaul and Forecasted Summer Load (8-14 August 1983) Using 20-hour Lag Time Effect for Temperature Variable

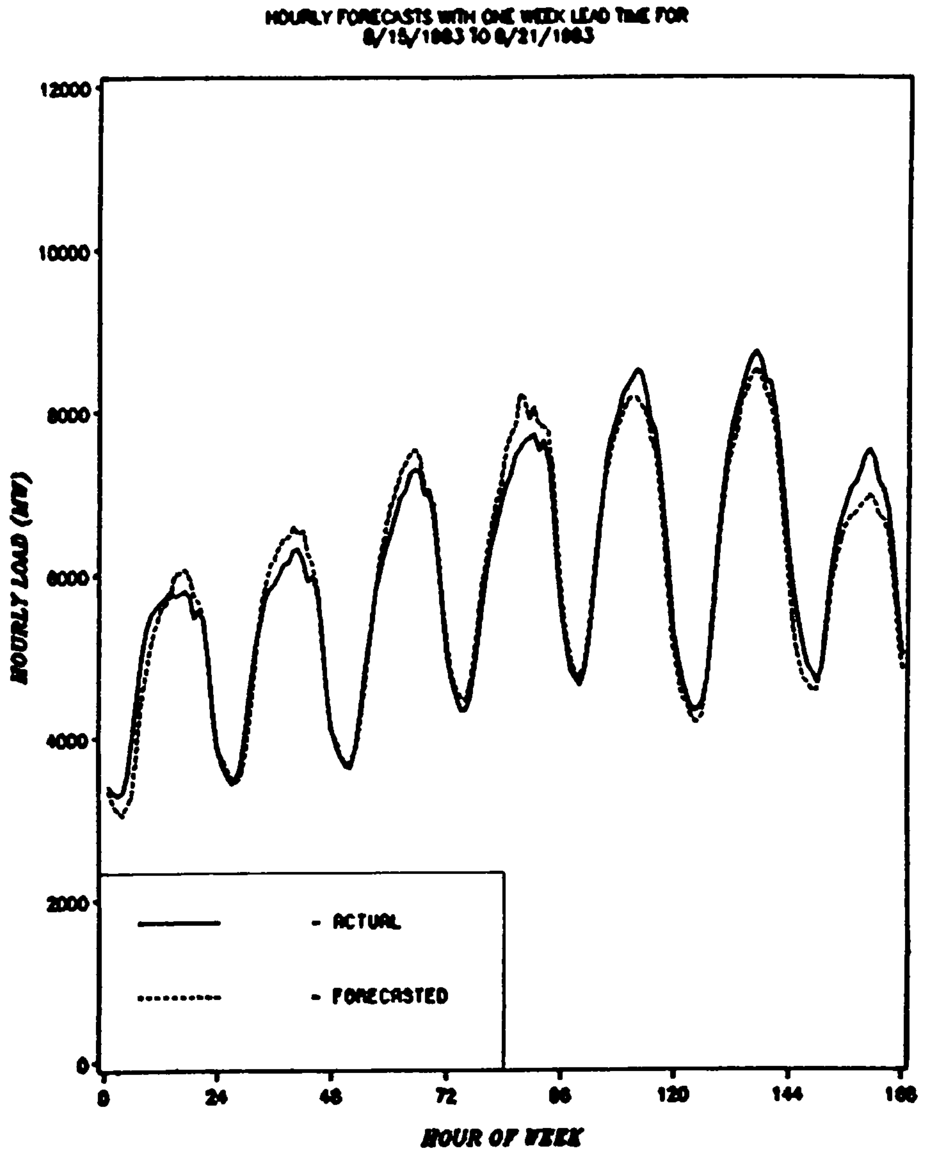


Figure 23. Actaul and Forecasted Summer Load (15-21 August 1983) Using 20-hour Lag Time Effect for Temperature Variable

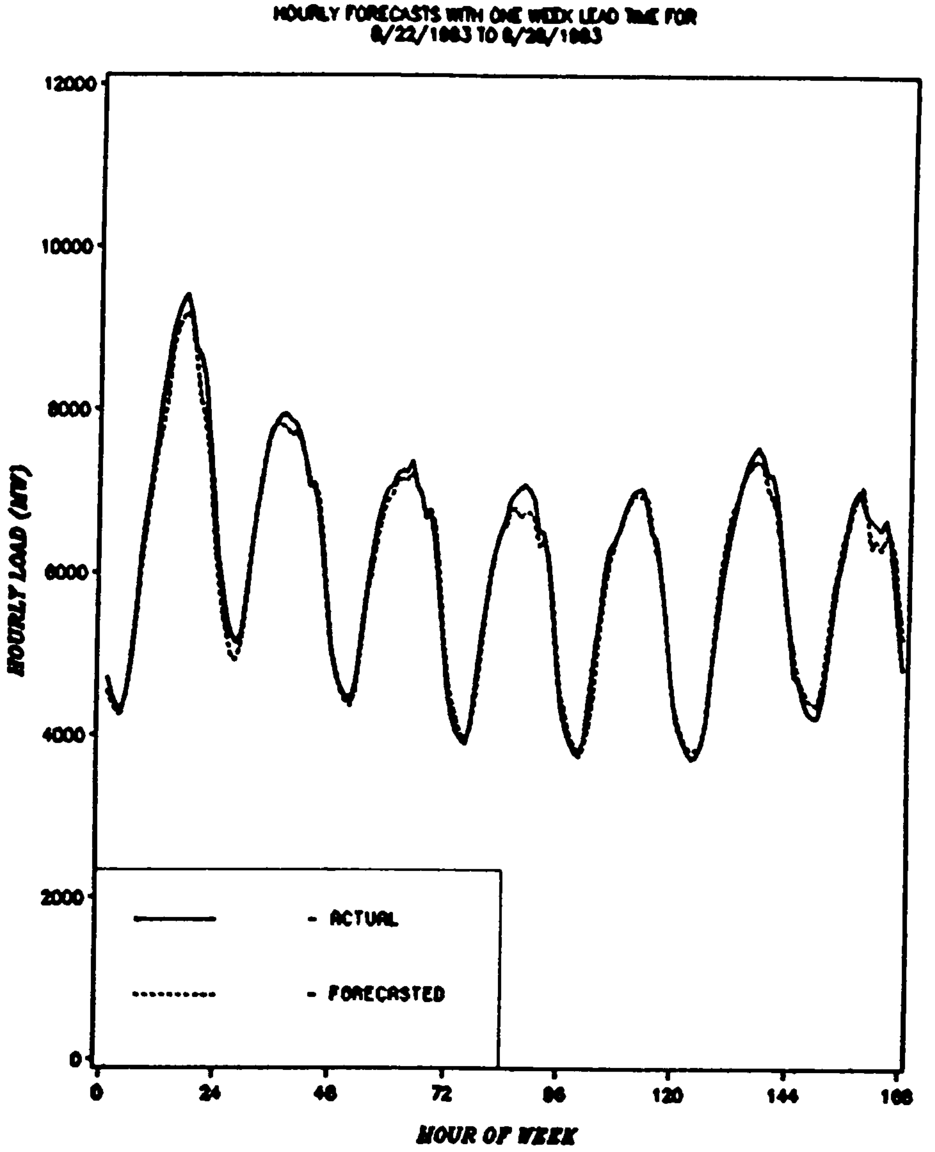


Figure 24. Actaul and Forecasted Summer Load (22-28 August 1983) Using 20-hour Lag Time Effect for Temperature Variable

Table 14. Absolute MW Daily Peak Load Forecast Error Statistics for Different Lag Time Temperature Effect

lag time (hours)	forecast error average	forecast error st. dev.	forecast error |max value|
1	295.50	231.35	915.71
4	301.59	202.17	821.08
8	260.71	176.84	815.29
12	231.49	156.11	716.92
16	224.59	130.55	636.22
20	216.14	122.66	548.80
24	214.22	124.86	496.65

(peak load of the month = 9409 MW)

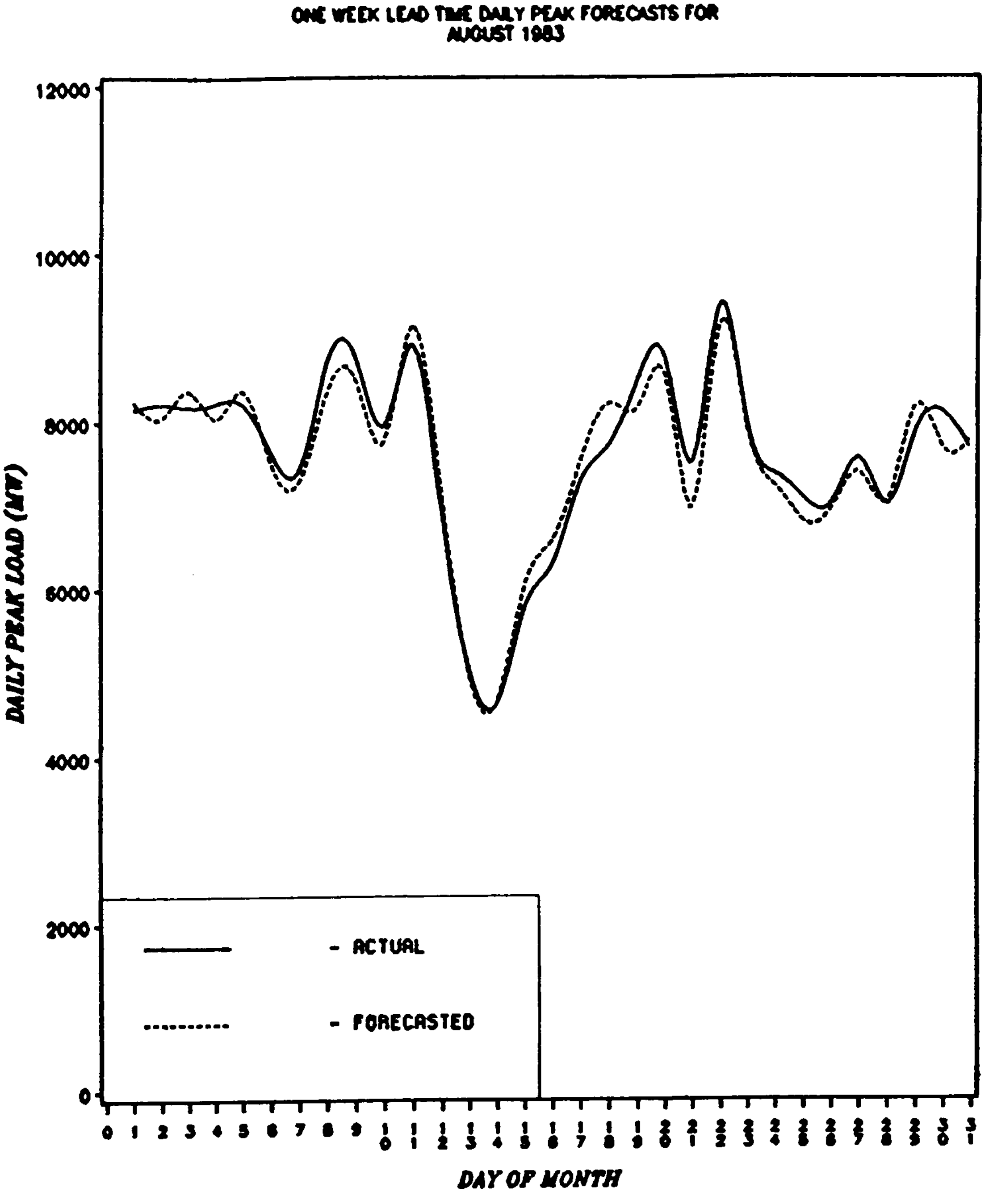


Figure 25. Actaul and Forecasted Summer daily Peak Load (1-31 August 1983) Using 20-hour Lag Time Effect for Temperature Variable

statistical techniques. This developed approach is implemented using a microcomputer. This work is considered as a part of a comprehensive load forecasting system. The development and performance evaluation of this load forecasting system is presented in chapters 8 and 9.

Chapter VII

EVALUATION OF SHORT-TERM LOAD FORECASTING TECHNIQUES

7.1 Introduction

Different forecasting techniques have been applied to the problem of daily load forecast. Almost all of these techniques fall in the realm of statistical techniques. The exception to this is a recent approach introduced by Rahman and Bhatnagar [2] which is based on applying a knowledge-based algorithm to the short-term load forecasting problem. Another algorithm that has applied the expert system approach is the work of Jobbour et. al. [3].

In this chapter a comparative evaluation of five short-term load forecasting techniques is presented. These techniques are:

1. Multiple Linear Regression;

2. Stochastic Time Series;

3. General Exponential Smoothing;

4. State Space Method; and

5. Knowledge-Based Approach.

Algorithms implementing these forecasting techniques have been programmed and applied to the same database for direct comparison of these different techniques. A comparative summary of the results is presented to establish an understanding of the inherent level of difficulty of each of these techniques and their performances.

7.2 Implementation of the Algorithms

The five forementioned algorithms have been applied to obtain hourly load forecasts (for up to 24 hours) during the winter and summer peaking seasons. Thus the five forecasting methodologies have been applied to the same database and their performances are directly compared. Specifically these five forecasting techniques are implemented to predict the hourly load of a southeastern (US) utility. For this purpose a summer peak day and a winter peak day are chosen. The model built for predicting these peak days, as applied to this utility, are discussed in the next section (i.e., section 7.3 through 7.7).

7.3 Multiple Linear Regression (MLR)

In the MLR application, the hourly load is modeled as: (i) Base Load Component which is assumed constant for different time intervals of the day and (ii) Weather Sensitive

Component which is a function of different weather variables. These weather variables include dry bulb temperature, dew point temperature and wind speed. The relationship between the weather sensitive component and most of the weather variables is not linear, but are rather transformed from current and previous lag time values.

The summer model for the hourly load at each of the considered time intervals has the form:

$$\begin{aligned} y_i(t) = A_i &+ B_i(T_d(t) - T_{ci}) + C_i(T_d(t) - T_{ci})^2 + D_i(T_d(t) - T_{ci})^3 + E_i(T_p(t) - T_{pi}) \\ &+ F_i(T_{ava} - T_{avb}) + G_i(T_d(t) - T_d(t-1)) + H_i(T_d(t-1) - T_d(t-2)) \\ &+ I_i(T_d(t-2) - T_d(t-3)) \end{aligned} \tag{7.1}$$

Similarly, the winter model for the hourly load at each of the considered time interval in this season has the form.

$$\begin{aligned} y_i(t) = A_i &+ B_i(T_{ci} - T_d(t)) + C_i(T_{ci} - T_d(t))^2 + D_i(T_{ci} - T_d(t))^3 + E_i(T_{pi} - T_p(t)) \\ &+ F_i(T_{ava} - T_{avb}) + G_i(T_d(t) - T_d(t-1)) + H_i(T_d(t-1) - T_d(t-2)) \\ &+ I_i(T_d(t-2) - T_d(t-3)) + J_i(W_c(t)) + K_i(W_c(t-1)) + L_i(W_c(t-2)) \end{aligned} \tag{7.2}$$

where, the wind chill factor, [105]

$$W_C(t) = 33 - [10.45 + 10\sqrt{0.477v(t)} - 0.447v(t)]\mathrm{x}[(33 - 0.556(T_d(t) - 32))/22.04] \tag{7.3}$$

and where

y_i(t)	=	load at hour t in the interval i of the day.
A_i	=	base load component (regression constant coefficient)
B_i through L_i	=	regression coefficients of weather sensitive component
T_d(t)	=	dry bulb temperature at time t, deg. F

(which will be clamped at the cut off value if necessary)

$T_p(t)$ = dew point temperature at time t, deg. F

(which will be clamped at the cut off value if necessary)

T_{ava} = average dry bulb temperature of previous 24 hours to the time t, deg. F

T_{avb} = T_{ava} lagged 3 hours, deg. F

T_{ci} = cut off dry bulb temperature for the interval i in the season, deg. F

T_{pi} = cut off dew point temperature for the interval i in the season, deg. F

v (t) = wind speed at time t, miles/hour

The model parameters have been found for both the summer and the winter weekdays as shown in Table 15 and Table 16 respectively. These parameters have been estimated using 4 weeks of weekday hourly data for each time interval. This was done in order to avoid picking up inter-seasonal variations. It must be noted that the division of the day into six unequal times zones is based on the authors' experience with the characteristics of the load shape of this particular utility.

7.4 Stochastic Time Series (STS)

The time series approach has been applied to model the hourly load data for both the summer and the winter seasons. Both seasonal ARIMA and TF models have been developed using 4 weeks of hourly data. The ARIMA model has been identified and its parameters estimated as:

$$(1 - 0.37B - 0.23B^2 + 0.11B^3 + 0.09B^{12} + 0.10B^{14} - 0.10B^{20})(1 - 0.12B^{24})\times$$

$$(1 - 0.32B^{168})\nabla_1\nabla_{24}y(t) = (1 - 0.91B^{24})a(t) \qquad (7.4)$$

Table 15. Weekday MLR Summer Model Parameter Estimates for Different Time Intervals of the Day

Parameter	Day Time Interval					
	12-4AM	5-9AM	10AM-1PM	2-5PM	6-8PM	9-11PM
A_i	2454.75	3733.13	3823.36	3001.17	3180.40	2500.89
B_i	75.28	70.88	-	-	-	-
C_i	-	2.20	6.55	9.16	7.46	8.22
D_i	-	-	-0.09	-0.14	-0.12	-0.15
E_i	48.26	20.40	52.60	42.57	69.03	45.73
F_i	-94.35	-138.60	-556.32	-444.19	-328.45	-320.88
G_i	-109.64	78.41	-55.75	-91.01	-145.43	-143.76
H_i	-88.31	-	-	-63.99	-83.80	-194.78
I_i	-56.50	-	-	-38.83	-	-76.23
T_{ci}	60	60	60	60	60	60
T_{pi}	50	50	50	50	50	50
RMSE	170.94	294.47	225.87	159.86	159.26	305.10
R^2	0.925	0.911	0.943	0.977	0.976	0.908

Table 16. Weekday MLR Winter Model Parameter Estimates for Different Time Intervals of the Day

Parameter	Day Time Interval					
	12-4AM	5-8AM	9AM-12PM	1-4PM	5-7PM	8-11PM
A_i	2697.67	4771.79	2931.22	3879.89	5502.75	4417.67
B_i	96.35	-	70.15	-	-	-
C_i	-2.84	1.01	-	2.82	1.39	1.00
D_i	0.08	-	0.005	-0.02	-	-
E_i	7.38	-	-	13.50	-7.93	-
F_i	72.74	-	144.14	106.84	-	-
G_i	45.32	-	-	-	-	-
H_i	34.74	-	-	-	-	-
I_i	-	-	-	-	-	-154.12
J_i	6.08	-	4.76	6.53	-	-
K_i	-	-	-	-	-5.19	-
L_i	-	-	4.40	-	-5.02	-
T_{ci}	50.00	70.00	70.00	70.00	70.00	70.00
T_{pi}	40	-	-	60.00	60.00	-
RMSE	84.73	693.38	122.84	135.37	164.67	513.49
R^2	0.982	0.445	0.955	0.934	0.919	0.479

The TF model has been identified and estimated using the same data with the input as the dry bulb temperature and is expressed as:

$$y(t) = (1.94 - 5.25B)x(t) + \frac{(1 - 0.93B^{24})a(t)}{\nabla_1\nabla_{24}(1 - 0.35B - 0.22B^2 + 0.10B^3 + 0.07B^9 + 0.09B^{12} + 0.11B^{14} - 0.94B^{20})(1 - 0.12B^{24})(1 - 0.33B^{168})} \quad (7.5)$$

The seasonal ARIMA and TF models were also developed for the winter season using 4 weeks of hourly load data. These are expressed respectively as:

$$(1 - 0.16B - 0.25B^2 + 0.11B^6 + 0.15B^7)\nabla_1\nabla_{168} = (1 - 0.60B^{168})a(t) \quad (7.6)$$

and

$$y(t) = (-2.847 - 6.554B)x(t) + \frac{(1 - 0.60B^{168})a(t)}{\nabla_1\nabla_{168}(1 - 0.13B - 0.24B^2 + 0.12B^6 + 0.15B^7)} \quad (7.7)$$

7.5 General Exponential Smoothing (GES)

The general exponential smoothing technique has been applied to model the hourly load for both the summer and winter seasons. Each model has been developed from a constant part, c, and a varying part that is a function of m frequencies with a daily periodicity. These models can be written as:

$$y(t) = c + \sum_{c=1}^{m}(a_i \sin w_i t + b_i \cos w_i t) \quad (42)$$

where

$$W_i = \frac{2\pi}{24} K_i$$

K_i has to a positive integer less than half the daily period (i.e. 12).

The fitting function can be expressed in the form

$$f(t) = \begin{bmatrix} 1 \\ \sin w_1 t \\ \cos w_1 t \\ . \\ . \\ \sin w_m t \\ cos w_m t \end{bmatrix} \tag{7.8}$$

An extensive analysis using hourly data for five previous weekdays has been performed to find the best fitting function parameters (m and k) and smoothing constant ($\alpha = 1 - \omega$) of the model. The best suitable parameters for the GES model for both summer and winter are as shown in Table 17.

7.6 State Space Approach (SS)

The state space algorithm has been applied to model the hourly load for both summer and winter days. Such an application has been performed on a special state space realization, namely canonical realization using stationary ARMA model. This means the

Table 17. General Exponential Smoothing Summer and Winter Model Estimates

Parameter	Summer Model	Winter Model
m	11	11
K_i	1,2,..,11	1,2,..,11
α	0.025	0.025
RMSE	189.7	168.2

modeled series has to be transformed into stationary series prior to modeling, if required. This transformation has been performed for both the summer and winter models. An hourly and daily differencing has been applied to the summer series and an hourly and weekly differencing has been applied to the winter series. The state space model has been obtained for the summer model as:

$$X(K+1) = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -0.234 & 0.077 & 1.114 \end{bmatrix} X(K) + \begin{bmatrix} 1 \\ 1.307 \\ 1.565 \end{bmatrix} a(t+1) \tag{7.9}$$

$$Z(K) = [1 \quad 0 \quad 0] \quad X(K)$$

(7.10)

where

$$X(K) = \begin{bmatrix} y(t/t) \\ y((t+1)/t) \\ y((t+2)/t) \end{bmatrix}$$

For the winter model, the state space model has been identified and estimated as:

$$X(K+1) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -0.280 & -0.037 & 0.558 & 0.560 \end{bmatrix} X(K) + \begin{bmatrix} 1 \\ 0.148 \\ 0.263 \\ 0.164 \end{bmatrix} a(t+1) \tag{7.11}$$

$$Z(K) = [1 \quad 0 \quad 0 \quad 0] \quad X(K) \tag{7.12}$$

where

$$X(K) = \begin{bmatrix} y(t/t) \\ y((t+1)/t) \\ y((t+2)/t) \\ y((t+3)/t) \end{bmatrix}$$

7.7 Knowledge-Based Expert System (KBES)

An example demonstrating this approach is a rule-based algorithm (implemented in this work) which is based on the work of Rahman and et. al. [85,106]. This algorithm consists of functions that have been developed for the load forecast model based on the logical and syntactical relationship between the weather and prevailing daily load shapes in the form of rules in a rule-base. The rule-base developed consists of the set of relationships between the changes in the system load and changes in natural and forced condition factors that affect the use of electricity. The extraction of these rules was done off-line, and was dependent on the operator experience and observations by the authors in most cases. Statistical packages were used to support or reject some of the possible relationships that have been observed.

The rule-base consisted of all rules taking the IF-THEN form and mathematical expressions. This rule-base is used daily to generate the forecasts. Some of the rules do not change over time, some change very slowly while others change continuously and hence are to be updated from time to time.

Application of the knowledge-based approach is based on the work of Rahman and et. al. [85,106]. In this application, the model of the hourly load using the expert system algorithm is based on selecting a reference day load curve according to a set of rules. This reference day is then reshaped according to other sets of rules as to account for (1) the expected variations in the forecasted day from that of the reference day, and (2) the variations in the impact of weather change on the load from day to the next. The load at hour h of the forecasted day is calculated as:

$$y_h^{FF} = y_h^{F1} + \Delta y_h \tag{7.13}$$

$$y_h^{F1} = y_h^{Rm} + \Delta y_h^{in} \tag{7.14}$$

$$\Delta y_h^{in} = (y_{00}^{T} - y_{00}^{R}) \times (24 - h)/24 \tag{7.15}$$

$$\Delta y_h = \pm \Delta t \times F1 \times F2 \times 25\,, \quad \Delta t \leq 10°F \tag{7.16}$$

$$\Delta y_h = \pm \frac{\Delta t^2}{4} \times F1 \times F2\,, \quad \Delta t > 10°F \tag{7.17}$$

where,

$+$ in summer

$-$ in winter

and where,

y_h^{FF} = forecasted load at hour h of the day

Δy_h^{in} = load correction due to inertia at hour h

y_{00}^{T} = load at hour 00 of the target day

y_{00}^{R} = load at hour 00 of the reference day

h = hour of the day for which forecast is sought

y_h^{F1} = 1st level forecast of load for hour h

y_h^{Rm} = reference day's load for hour h modified to to account to the day to day variations

Δt = ambient (or effective) temperature difference between hours in forecasted and reference days.

F1 = weighing factor that account for the relative change in temperature between the forecasted and reference days

F2 = weighing factor that account for the different reference day temperatures

The rules governing F2 is changing continuously and therefore a revising mechanism has been developed to update these rules automatically [106].

7.8 Comparative Summary of Results

This section presents a summary of the results of applying the five load forecasting techniques to a typical southeastern (US) utility. Because of high heating and air conditioning loads this utility experiences high demand in both winter and summer. In order to check how well the implementations of these five forecasting techniques work, they have been applied to predict the daily load (up to 24 hours) on winter and summer peak days. The error analyses are provided in Tables 18 and 19 for the winter and summer days respectively. As these results are based on forecasts of two single days, these should be used for comparative purposes only.

Table 18. Forecast Percent Error for Summer Using the Five Load Forecasting Algorithms

Time	Load	MLR	STS		GES	SS	KBES
			ARIMA	TF			
1	4946.	1.79	.08	.07	1.11	.31	-.33
2	4757.	-.15	.15	.18	1.44	.77	.33
3	4600.	-1.28	-.67	-.53	1.14	.24	.02
4	4586.	-.92	-.93	-.74	1.43	.20	.25
5	4756.	1.91	-.77	-.57	1.34	-.24	-.25
6	5196.	-5.01	.20	.37	1.78	-.05	-.33
7	5809.	1.18	.67	.80	1.88	-.08	-.55
8	6261.	3.14	-.84	-.81	.06	-2.56	-1.26
9	6847.	4.34	.06	-.02	1.49	-1.34	-1.27
10	7106.	.57	-1.16	-1.36	.27	-2.78	-1.69
11	7527.	.20	.13	-.13	1.35	-2.57	-1.52
12	7693.	-1.59	.07	-.28	.77	-3.75	-1.43
13	7698.	-5.80	-1.64	-2.09	-.16	-3.26	-1.43
14	7972.	-4.02	.45	-.05	2.22	.09	-2.30
15	8082.	-.79	.93	.47	3.17	1.57	-1.49
16	8214.	1.41	1.36	.95	4.03	2.96	-2.65
17	8180.	2.46	1.04	.70	4.27	3.36	-2.40
18	7937.	1.85	-.39	-.67	2.93	1.74	-2.75
19	7559.	1.18	-.70	-.95	2.55	1.48	-1.60
20	7467.	4.55	.32	.14	3.44	1.45	-1.93
21	7284.	6.17	.06	-.11	3.53	1.34	-.16
22	6724.	10.02	.23	.10	3.56	1.49	-.11
23	5989.	4.01	.05	-.05	3.38	2.17	1.97
24	5402.	-2.34	.14	.09	3.59	1.97	1.19

Table 19. Forecast Percent Error for Winter Using the Five Load Forecasting Algorithms

Time	Load	MLR	STS		GES	SS	KBES
			ARIMA	TF			
1	4229.	1.75	.77	.62	-.90	.32	-.10
2	4124.	-.31	1.86	1.64	-.24	.43	.10
3	4107.	-2.06	2.77	2.12	-.50	1.12	1.29
4	4182.	-.68	3.95	3.38	.11	2.01	1.61
5	4315.	-.58	4.85	4.49	.02	2.56	2.08
6	4738.	-18.71	4.50	4.31	-.45	2.83	1.30
7	5842.	-1.88	6.19	6.17	.81	5.40	1.22
8	6558.	8.68	6.67	6.75	.54	7.10	2.18
9	6432.	7.47	4.97	5.09	-1.33	4.27	1.58
10	6149.	-2.04	2.34	2.46	-2.99	1.05	.47
11	5879.	-2.40	.83	.47	-4.63	-.16	-2.42
12	5688.	-3.90	.35	-.44	-4.44	-.43	-1.44
13	5463.	-4.98	-.78	-1.84	-4.25	-.85	-.98
14	5303.	-3.17	-.77	-2.09	-4.43	.09	-1.03
15	5219.	-3.03	-.62	-1.75	-3.55	-.15	.09
16	5138.	-3.69	-.50	-1.49	-2.87	.83	.65
17	5364.	-.95	-.50	-1.56	-1.17	1.81	1.25
18	5889.	-3.18	-1.56	-2.78	-.59	1.60	1.74
19	6277.	-.18	-.29	-1.56	-.54	1.46	1.49
20	6156.	-3.80	-.42	-1.72	-.02	.94	.85
21	5921.	3.18	-1.11	-2.33	-1.15	-.36	1.84
22	5597.	-.19	-1.82	-3.11	-1.46	-1.16	1.67
23	5115.	-4.41	-2.16	-3.64	-2.69	-2.50	1.52
24	4628.	-9.07	-1.49	-3.00	-3.26	-1.50	2.10

Some interesting observations are made about the results presented in Tables 18 and 19. For example, for the peak summer day the transfer function (TF) approach gave the best result, whereas for the peak winter day the TF approach resulted in the next to the worst accuracy. During the peak summer day the temperature profile was typical whereas during the peak winter day the profile was unseasonal. Thus one can see that because of its strong dependency on historical data, the TF approach could not take into account abrupt changes in weather as efficiently as others, like the knowledge based expert system (KBES).

7.9 Conclusion

This chapter is based on the comparative analysis of five short-term load forecasting techniques. During the implementation of these techniques certain interesting properties of the load and the variables have been observed. For example, for the multiple linear regression (MLR) technique the day was divided into six unequal time zones. This gave a much better fit than not dividing the day, or dividing the day equally. Probably because of this division strong correlations were found between the load, the dry bulb temperature, dew point temperature, and wind speed. On the other hand, when the transfer function (TF) model was built, results did not show any significant cross-correlation between the load and these variables, with the exception of the dry bulb temperature. The forecast for the TF approach was based on the historical load and temperature, and the future temperature as forecasted by the temperature model itself. This has a benefit, because of the internally generated temperature forecast the weather prediction error would not contaminate the load forecast. On the other hand if any significant changes in the weather are expected the model cannot use this information unless forced to do so externally. This may cause higher errors. It may be noted that the non-linearity that caused the unequal division of the day for the MLR technique was detected through the authors' experience with the load characteristics. The characterization of such nonlinearities is not an intrinsic property of either the multiple linear regression (MLR) or the transfer function (TF) technique.

Chapter VIII

AN INTELLIGENT LOAD FORECASTING SYSTEM

8.1 Introduction

In previous chapters the application of two distinct modeling methodologies, the statistical and the knowledge-based approaches, have been presented. Each of these modeling modeling methodologies has its benefits and limitations. For example, the knowledge-base approach has the ability of being very adaptive. This ability could be obtained by building a knowledge-base that is capable of accounting for the various foreseen changes in the load forecast process. The statistical approaches have the ability of systematically extracting the trend that is contained in the historical load process possibly with other dependent processes such as those of explanatory weather variables. Another example, the knowledge-base approach suffers from some limitations. One of these limitations is that the load predictions will depend on how comprehensive the knowledge-base is for the load forecast model. The statistical approaches also have their own limitations. One of these limitations is their inability to adapt for changes in the load forecast process as a result of seasonal variations and a a result of internal or external variables.

In this chapter, a system is proposed that can integrate both of the statistical and the rule-based modeling methodologies. Such a hybrid system could outperform the individual performance of the statistical or the knowledge-based approach. This outperforming could be attributed to benefitting from the capabilities and overcoming the drawbacks of these techniques. It is believed that this system will have the attractive features of both the statistical and the rule-based approaches where both can be utilized. The performance of this load forecasting system is evaluated in the next chapter.

The work presented in this chapter is devoted to cover the development of this hybrid (comprehensive) load forecasting system. First, the objective behind the development of this system is covered in section 8.2. This is followed by a discussion of the structure of load forecasting system as covered in section 8.3. The development of the load forecast system and its components are covered in section 8.4 through section 8.6. Discussion of the two essential components for any intelligent system (i.e., knowledge acquisition and knowledge-base components) are provided in section 8.5 and section 8.6. Finally, section 8.7 covers a summary about the work presented in this chapter.

8.2 Objective of the Load Forecasting System

The load forecast process is not a final product by itself. It is an input process to other decision making of the electric utility operations. As previously mentioned and discussed in chapter 3, the load forecast is the dynamo behind which most if not every utility operation is derived. This interrelation has been shown in Figure 1. This includes The following:

- Load (economic) dispatch
- Generation unit commitment
- Energy transfer scheduling

- Coordination of the energy management programs with the system resources (demand side management and dispersed generation and storage)

Therefore, the main objective of this load forecasting system is to enable the user (utility operator) to produce the different lead-time (hourly and daily peak) load prediction that are necessary for carrying successfully and economically the fore-mentioned utility operations.

8.3 Load Forecasting System Structure

The concept of any load forecasting system is to model the load process using its historical data and possibly with other explanatory variables. This model is then used to project the load process into the future and provide estimated load predictions to the desired lead time. A simple diagram showing the main components of a load forecasting system structure is shown in Figure 26. Description of each of these components are presented in the following:

8.3.1 Data base

This comprises the most recent information about the load data and other influencing variable such as dry bulb temperature, humidity, wind speed and others. This information is collected usually on a continuous basis through communication channels (i.e. modem communication and/or hard wire connections) from their sources (i.e. load from generating stations and meteorological data from weather stations). This information could also be supplied manually by the user (utility operator) through a terminal keyboard. Usually the collected information is filtered, stored and archived to be readily retrieved by the proper programs or techniques in the load forecasting system. This process of acquiring and managing data is not a subject of study in this work. Such topics have been addressed in the

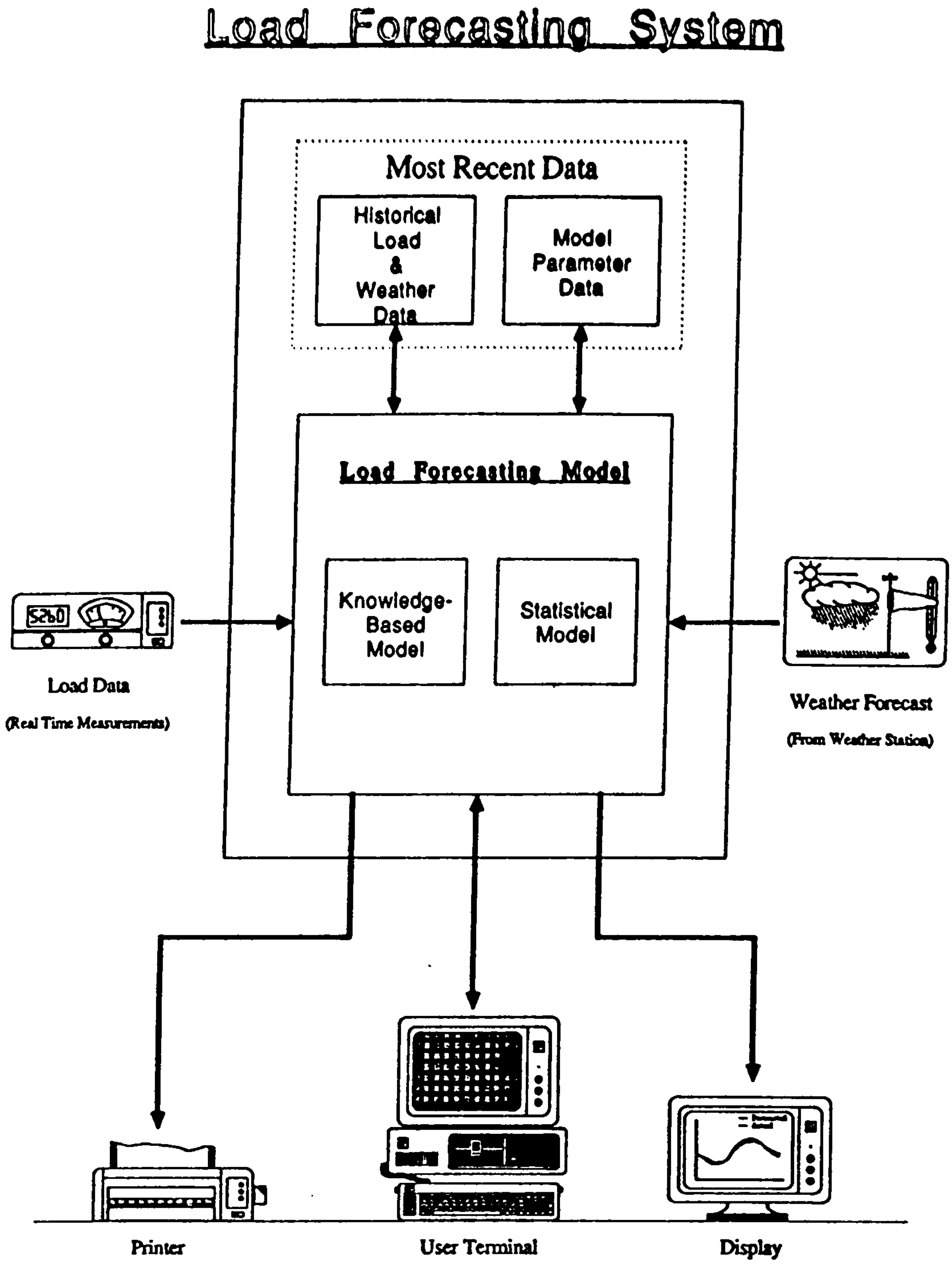


Figure 26. Structure of a Load Forecasting System

work of Rahman and Baba [84]. For the purpose of this study, the most recent load and meteorological information are assumed to be available and non-contaminated (clean), along with other needed future meteorological data.

8.3.2 Load forecast model

The load forecasts are obtained through some form of modeling of the load process. This load model is built using the data base which usually encounters the most recent information about the load and other influencing variables using quantitative (statistical) methods. The depth of expertise of the load forecaster plays an important part in building this forecast model. Load forecast domain experts can also supply a sufficient knowledge for building a load forecast model using qualitative (knowledge-base) methods. The model as indicted in Figure 26 could be built either using knowledge-based or statistical modeling methodologies. The knowledge-base and the various statistical modeling methodologies have been presented in previous chapters along with an evaluation and analysis for their performances.

8.3.3 Input/Output facilities

The input facilities are basically the tools that are used for supplying the load and weather information needed for modeling and forecasting the load. This information forms the data base. The facilities for supplying this information to the load forecasting system has been explained in section 8.3.1. That includes modem and hard wire communications. This information as well as other data needed by the system could also be inputted through a terminal keyboard. The output facilities includes the user terminal, possibly with other terminal to display the load prediction, and a printer to get a hard copy of the output of the system load forecast programs.

8.4 Development of the Load Forecasting System

This system is built using various load modeling methodologies which could be classifies as the best for short-term load prediction. The concept behind the development is to combine both of the statistical and the rule-based load modeling methodology under one load forecasting system. These various modeling methodologies will be developed to work under a knowledge-based (intelligent) load forecasting system. The major components of the structure of this load forecasting system is shown in Figure 27. Discussion of each of the two essential components of this intelligent load forecasting system and their functions are discussed in section 8.5 and section 8.6.

8.5 Knowledge Acquisition

Knowledge about the load process, the dependent variable processes, the cross-relationship between the load and the dependent variable processes, and the inter-relationship between these processes and the power system utility operations are required. Also knowledge about model building and forecasting using the various techniques used are required. This required knowledge is explained in depth in section 8.6 (i.e. the knowledge-base). The process of knowledge acquisition has been explained in section 4.4.3.

The author has performed the task of that of the knowledge engineer and processed the information provided by the domain expert. The tools that have been used for acquiring the knowledge needed for developing the knowledge-base of this load forecasting system are the following:

- performing exploratory data analysis: This include plotting and other means of understating the load and weather processes and the relationship between them in all seasons.

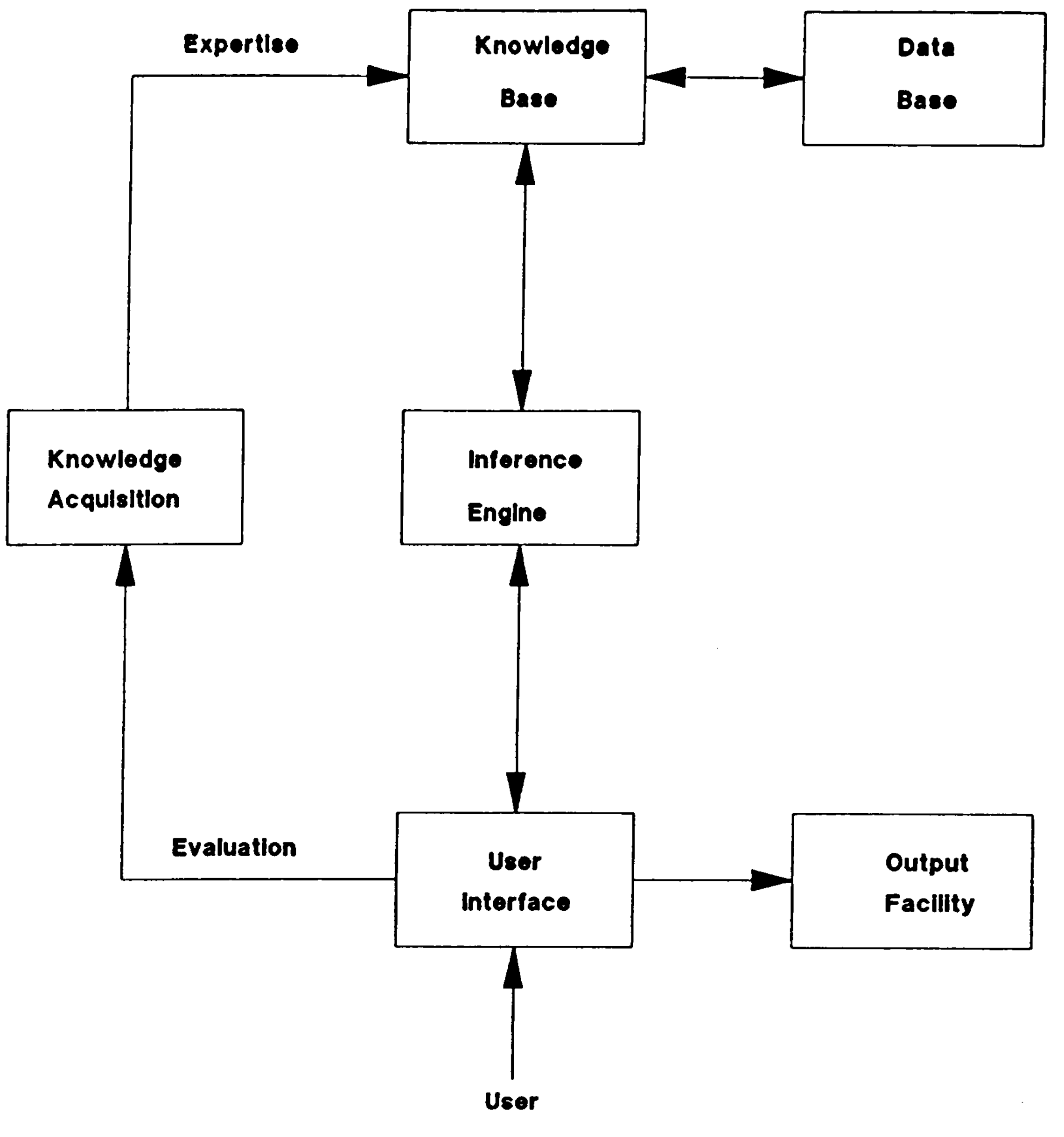


Figure 27. Components of the Load Forecasting System

- performing statistical analysis: This include mean-range plots, autocoorrelation, partial autocorrelation and crosscorrelation analysis, spectral analysis, and other useful statistical analyses.

- comprehending the various (implemented) modeling techniques: this includes understanding the procedures for the applications, the properties, the characteristics, and the capabilities and the limitations of these various modeling techniques

- performing manual analysis: this includes a careful data observation and hand calculations.

- importing expertise: this includes gathering knowledge and other information through discussion sessions with load forecast domain "EXPERTS".

- monitoring the system performance: this include tracking the forecast residuals along with other load and weather information along with other information that could help evaluating and improving the performance of the system.

8.6 Knowledge-Base

Building a knowledge-base is a dynamic process. This means the knowledge-base can be expanded as expertise about the system is increased. Starting at the current level of expertise, the knowledge-base is structured as shown in Figure 28. This Figure indicates that knowledge-base consists of several segment of knowledge about different aspects about this load forecasting system. The reason behind this partition is to make the task for tracking, expanding, and updating this knowledge-base easy for these different aspects. Each segment of this knowledge-base is briefly presented with some examples. Along with this presentation, the role of each component is discussed.

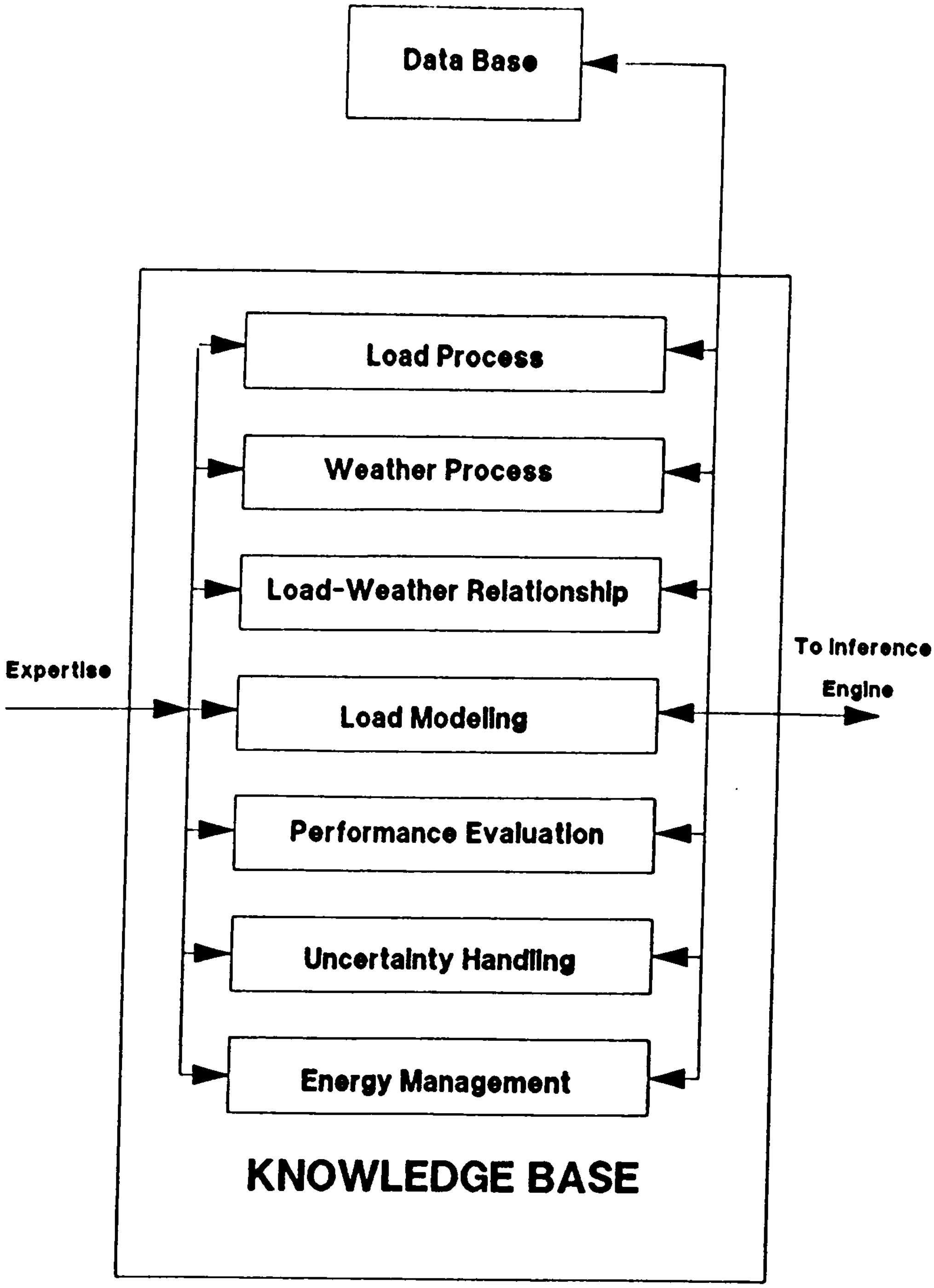


Figure 28. Knowledge-Base of the Load Forecasting System

8.6.1 Load process

This segment of the knowledge-base (KB) consists of the available information about the load processes. This includes the different forms of load information that are needed for the system such as hourly load, daily peak, daily average load, power factor, and load in hourly-intervals. This information usually encountered the most recent measurements of these variables that are sufficient for load model building and forecasting. This load information is provided with other needed knowledge which could be considered as indicator variable information such as hour-of-day (0-23), day-of-week (day type, 1-7), and date (day and month). This type of information are organized in the data base in different files. This type of information concerning the load process (different load and indicator variables) are facts that are built in the knowledge-base (i.e., data base which is accessed from within the knowledge-base). There are other facts that are built in the knowledge-base. This includes the known holidays. Other than this built in facts, there are other information concerning the load processes which are expressed using rules or heuristics. One group of rules is those for accessing the different load variables that are needed for building the load forecast model or prediction. These rules include: (1) opening the file that includes the right variable or variables, their position, and format. Such rules take the form of IF-THEN statements such as:

IF the predicted variable is hourly load
THEN open the file "hrlyload data"

IF the predicted variable is hourly load
  AND the file is "hrlyload"
THEN position starts at column 62
AND format is f8.2

The load processes knowledge-base segment can include knowledge about how load data are reduced during holidays compared to those in normal working days. For example,

IF the day is of the 4th of July
AND the day of the week is Tuesday through Friday
THEN the load (curve) will be reduced by 15 %.

This type of heuristics not only can be used in adjusting the predicted load variables, but also can be used as means of adjusting the historical data of these variables before using them in building the load forecast models.

The role of the load process knowledge can be summarized in the following:

- facilitating the retrieval of the required load variable process(es) for load modeling and forecasting by the system.

- removing of the effect of the variables that are not accounted for in the load forecast model building. The may include the effect of internal variables such as those action taken by load management programs.

- adjusting the predicted load values to account for variables that are not accounted in the load forecast model. This adjustment may include revising the predicted load values to account for the action of energy management programs.

- facilitating the storage and archival of the predicted load variable process(es) for future access by the system.

- facilitating the retrieval of the predicted load values. This process of retrieval is useful for evaluating the system performance by comparing these predicted values to the actual values in view of all the influencing variables. This process is also useful for accessing the predicted values in search for a and a suitable prediction that could be obtained in some form from these predicted values.

8.6.2 Weather process

This knowledge base (KB) segment includes information about the weather variables that are most likely to influence the various load processes. Such information is also needed with information about the indicator variables which include hour-of-day, day-type, and date. This weather and indicator variable information usually consists of the most recent historical data about these variables that matches the load processes data. Besides the historical weather data, other information concerning the future weather variable information is also needed for the prediction processes. This type of information is generated from within the system for some weather variables. Other variable future (predicted and actual) information about the weather variables is assumed available from generating sources outside the system. This information about the historical and the future weather and indicator variables are organized in the data base in different files that are accessed through this segment of the knowledge-base. This information constitute the fact part of this KB segment. Other knowledge is in the form of heuristics such as the rules for accessing certain weather variables. These rule, which are similar to the rules in the previous section, are designed for opening files, and for defining the format and position of the weather variables needed. Other heuristics are those concerning the forming of new weather variables that have a compound or more influencing effect under certain conditions. For example, the effect of temperature and humidity is summer can be combined using one variable called the temperature humidity index (THI). This variable then can replace the dry bulb temperature in modeling the temperature effect on load under certain conditions as:

IF it is summer

AND the dry bulb temperature is > 80 F .

THEN the temperature humidity index is needed.

The role of the weather process knowledge can be summarized in the following:

- facilitating the retrieval of the required weather variable process(es) for modeling and forecasting of these weather variable processes by the system.

- storing the predicted weather variables process that will be needed in the load prediction.

- facilitating the retrieval of the required weather variable process(es) for load modeling and forecasting by the system.

- adjusting of the weather variable process to reflect the actual influence on the load processes. This may include creating new weather variable from these variable that exist in the weather variable data base.

8.6.3 Load-weather relationships

This segment of the knowledge base consists of the information needed to identify the different weather variables that affect the different load processes. These identified weather variables are needed when a weather sensitive component has to be considered in the load forecast model building. Therefore, this segment of the knowledge includes rules for selecting the necessary weather variable(s) in the different seasons, their cut off values, their inertia effect, and possibly their daily hour-interval effect with weather variable magnitude-interval effect. This may include rules about the order of significance of these explanatory variables. Other rules includes the use of compound weather variables such as temperature humidity index (THI) and wind chill index (WCI) where the use of such variables can best describe the weather sensitive component of the load forecast model. For example, in summer the combination of temperature and humidity can best describe the relationship between the load and weather than the dry bulb temperature when the later exceeds certain value as:

IF the season is summer

AND the dry bulb temperature is > 80 F.

THEN the THI is needed instead of the DBT.

The role of the load-weather relationship knowledge can be summarized as:

- facilitating the identification of the different explanatory weather variables in the different seasons.

- adjusting the effect of the weather variables by creating new compound weather variables.

- specifying the peak and valley time intervals of load curve.

The above discussed aspect of load weather relationship addresses the relationship between the load in general (required generation) and meteorological data. There is another different aspect for the load weather relationship. This other aspect is the effect between the controllable loads , such as air conditioners and space heaters, and the weather variables. This aspect is important for the energy management programs that could be part of the load forecasting system. This aspect is addressed in section 8.6.6. For the part of this section, many rules could be developed to address the load-weather relations as affected by the controllable loads. Such work has been conducted in the Alternate Energy System Laboratory at Virginia Tech [84]. For example, the demand for air conditioning will rich a saturation value if the temperature humidity index is greater than 88 F.

8.6.4 Load modeling

This segment of the knowledge base consists of the knowledge about the different modeling techniques and the different processes that could be modeled. The modeled processes are mainly those of the different load variables, but some weather variables processes are also modeled using similar techniques to those used to model some of the load processes. Both the statistical (quantitative) and the knowledge-base (qualitative) techniques are used for building models for the load processes, while some of the weather processes are built using statistical techniques only. These techniques and the models built using them at the current state are as follows:

- Univariate time series (Box and Jenkins) approach

    1. hourly load
    2. hourly dry bulb temperature
    3. daily average load (energy)
    4. daily average dry bulb temperature
    5. daily peak load
    6. daily peak load factor
    7. daily peak load dry bulb temperature
    8. daily hour type load
    9. daily hour type dry bulb temperature
    10. daily (minimum/maximum) to average dry bulb temperature

- Transfer function time series (Box and Jenkins) approach

    1. hourly load

2. daily average load (energy) forecast.

3. daily peak load

4. daily hour type load

5. daily load factor

- Multiple linear regression

1. daily average load (energy) forecast.

2. daily peak load

3. daily peak range load

- Knowledge base approach

1. hourly load

2. daily peak load

3. daily peak range load

- simple models

1. average daily load curve

2. average load factor (at peak)

This type of information concerning the load modeling (different load models and techniques) are facts that are built in the knowledge-base (i.e., data base which is accessed from within the knowledge-base). Each of the previous mentioned models has information about its structure and variables. This includes the model the needed differencing or centering of the data, the identified variables (parameters) with their estimates and confidence and their locations. Such information are stored in files that are accessed through this segment of knowledge base. Other than this built in facts, there are other information concerning the load modeling which are expressed using rules or heuristics. One group of rules is those for accessing the different load models that are needed for issuing the different load predictions. These rules include: (1) selecting the appropriate model or models. (2) opening the files that contains the model parameter estimates and various needed inputs that are stored in the system. An example of these rules is the following.

IF the predicted variable is hourly load

AND the season is SPRING

THEN use the univaraite time series model

An other example is

IF the model is model is univariate

AND the season is SPRING

THEN open the files defining this model

AND open the files containing the model parameters and other needed data

The role of the load modeling knowledge can be summarized in the following:

- facilitating the selection of the different needed load models.
- facilitating the retrieval of the different needed data for the selected load models.
- facilitating the display and the storage of the generated predictions.

8.6.5 Performance evaluation

This segment of the knowledge base consists of the knowledge for monitoring and tracking the performance of the different load modeling that are applied. This includes tracking the forecast residuals of both the load and explanatory variables. This also include tracking the conditions at which each model is valid at. This may require testing the significant of model parameters, reestimating their values and possibly altering the model structure and reevaluating its parameters. The fact part of this segment of the knowledge base consists of all the assumptions, capabilities and limitations at which the different models are applied. For example, a rule concerning the stationarity of the hourly load series in winter can be expressed as:

IF the load series is hourly
  AND the season is winter
THEN perform a daily and a weekly differencing to make the series stationary

Another example, a rule for the validity of the transfer function models in summer is can be stated in the following.

IF the season is summer
  AND the daily peak temperature is above 72 deg. F
THEN the transfer function models can be applied.

The role of the performance evaluation knowledge can be summarized in the following:

- facilitating the monitoring of the actual and predicted data in order to determine the forecast accuracy as new observations become available.

- facilitating the monitoring of the actual and predicted data in order to explain their residuals and variations with respect to the considered explanatory variables as time changes.

- facilitating the testing of the validity of the assumptions at which the models are applied.

- facilitating the testing of the validity of the conditions at which the models are applied.

- facilitating the tracking of the validity of the structure of the applied models and signaling when this structure needs to be altered or its parameters needs to be reestimated.

- facilitating the retrieval of the different needed data for the selected load models.

8.6.6 Uncertainty handling

This segment of the knowledge base consists of the knowledge that can be used in calculating the reliability of the forecasts produced. This reliability is expressed in terms of confidence limits as deviations or percent values around the point estimate of the predicted variables. Usually, the statistically based models can be built with confidence intervals (variances) for their parameters and an overall error variance for the model as whole. The variances of the model parameters give a measure of the uncertainty in these parameters and the variance of the error of estimation gives an overall index summarizing the uncertainty contained in the developed models. For the knowledge based models, the degree of risk or uncertainty is usually obtained from the forecast domain experts along with the facts, rules and expressions for the model building. In either of the modeling approaches, facts of uncertainty of the model predictions can be built in this segment of the knowledge base. Rules or heuristics can also be built to access these facts in order to enable the calculation of the confidence of the produced forecasts by the load forecasting system. This can be done as the amount of deviations or the percent variations associated with the forecasts. For example, the lead time variance of the forecast error of a univariate model of the daily peak in spring can be calculated by searching for the order of the model and the estimates of its parameters and error standard deviation. Then using the variance of the forecast error and the forest can be produced with a confidence intervals.

The role of the uncertainty handling knowledge can be summarized as:

- facilitating the retrieval of the appropriate needed data for calculating the prediction uncertainties.

- facilitating the calculations or provisions of the confidence intervals that are associated with the predicted values.

8.6.7 Energy management

This segment of the knowledge base consists of the information that is needed to integrate the energy management programs into the load forecasting system. By energy management programs is meant the process of altering the load curve by reducing the peak load or shifting it to other times where the available generation resources are capable of supplying the demand for electricity economically. This include load shedding such as air conditioning and water heaters and storage techniques such as pumped hydro or battery storage. These operations usually affect the load processes as well as the predictions. Therefore, integrating the effect of the energy management actions into the load forecasting system is essential for better modeling by removing the effect of the actions of the energy management system programs. It is also essential for accurate prediction where the actions of the energy management programs have to be accounted for in the issued forecasts.

The role of the energy management segment of the knowledge base is:

- Facilitating the removal of the effect of the energy management programs so the load processes are as natural as possible to get more accurate load models.

- Facilitating the corrections of the load predictions by accounting for the effect of the energy management programs on them.

8.7 Summary

An intelligent load forecasting system has been proposed in this chapter. This system will combine both statistical and knowledge-base modeling approaches to the load forecasting problem. This system is expected to have the advantages of both of these modeling approaches. The evaluation of this load forecasting system is presented in the next chapter.

Chapter IX

PERFORMANCE EVALUATION OF THE LOAD FORECASTING SYSTEM

9.1 Introduction

An intelligent load forecasting system has been presented in the previous chapter. Such system integrates both statistical and rule-based approaches. The evaluation of the performance of this system is presented in this chapter. This evaluation was simulated by developing the best statistical techniques as well as a knowledge base technique as covered in section 9.2. There are two methods for modeling the load, particularly the peak load. These methods are the power method and the energy method. Details of the models that were developed using each of these methods are covered in this section. Section 9.3 presents a discussion of the results of both the power and the energy methods using different statistical modeling techniques. A judgment was concluded of what method or technique to use in specific season or under specific weather conditions.

The focus of the remaining sections of this chapter was devoted to the one week lead time forecast. The reason behind this focus was that forecasts to one week time ahead are needed for unit commitment as well as energy management applications. It is also believed that this range has not been addressed significantly in the literature. The best of the previous models and techniques were used to address the one week lead time forecast in section 9.4. Then a weighted averaging method is presented in section 9.5 where the weights are supplied by load forecast domain experts. In parallel to this the rule base forecast present in chapter 6 is used to generate forecasts that are totally dependent on the system operator as presented in section 9.6. Finally in section 9.7 a conclusion about the work of this chapter is presented.

9.2 Simulation

For the purpose of evaluating the proposed intelligent load forecasting system, modeling and forecasting of both the hourly and the daily peak load have been performed using different techniques and different models. The knowledge used in applying these techniques and building the models were extracted from relationships between load and weather variables, other historical observations and perceptions of domain experts. The techniques and the models built using them at the current state are as follows:

- Univariate (UV) time series modeling
    1. hourly load
    2. hourly dry bulb temperature
    3. daily peak load
    4. dry bulb temperature at daily peak load
    5. daily average load (energy)
    6. daily average dry bulb temperature

7. daily average dew bulb temperature

8. daily load factor

9. daily (minimum/maximum) to average dry bulb temperature

- Transfer function (TF) time series modeling

    1. hourly load

    2. daily average load (energy)

    3. daily peak load

    4. daily load factor

- Multiple linear regression (LR) approach

    1. daily peak load

    2. daily peak range load

    3. daily average load (energy)

- Knowledge base (KB) approach

    1. hourly load

    2. daily peak load

- Simple averaging (SA) approach

    1. daily load curve

    2. load factor (at peak load)

The above models that were developed using different statistical techniques can be categorized according to the processed data as either power modeling method or daily energy modeling method. Each of this category of load modeling is examined in the next subsection.

9.2.1 *Power method*

In this method the hourly data or the daily peak load data (i.e. power data) were used to develop model that are capable of producing predictions for the hourly load and the daily peak load up to one week lead time. Different models were developed and simulated using different modeling techniques. These model are listed as the following:

Model 1: Hourly load model using load data only.

For this model the hourly load is predicted up to 168-hour lead time using univariate time series model.

Model 2: Hourly load model using load and weather data (prediction with accurate weather data).

For this model the hourly load is predicted up to 168-hour lead time using transfer function time series model. The dry bulb temperature is used as the input series variable, which is modeled using univariate time series.

Model 3: Hourly load model suing load and weather data (prediction using forecasted weather data)

This model is the same as model 2 but forecasted weather information is used in the 1 to 168-hour lead time load prediction.

Model 4: Daily peak model using peak load data only.

For this model the daily peak is predicted up to 7-day lead time using univariate time series model.

Model 5: Daily peak model using daily peak load and weather data (prediction with accurate weather data).

For this model the daily peak is predicted up to 7-day lead time using transfer function time series model. The dry bulb temperature at the hour of the peak load is used as the input variable. This input variable is modeled using univariate time series.

Model 6: Daily peak model using daily peak load and weather data (prediction using forecasted weather data).

This model is the same as model 5 but accurate weather weather information is used in the 1 to 7-day lead time load prediction.

9.2.2 Energy method

In this method the total energy requirement is predicted up to 7 days ahead. The daily peak is determined using a knowledge about the load factor along with the daily energy. The following formula is used to calculate the daily from the daily energy and the load factor predictions.

$$Peak \quad load = \frac{Daily \quad Energy}{24} x \frac{1}{Load \quad factor} \tag{9.1}$$

Depending on the technique for predicting the load factor and the total energy different models have been developed using this method: These models are as follows:

Model 7: Daily peak model using enegy data only with actual load factor values.

For this model the daily peak is predicted up to 7-day lead time using transfer function time series method for the energy model and the actual value (prefect prediction) of the load factor.

Model 8: Daily peak load model using energy and weather information (prediction using accurate weather data) with actual load factor values.

For this model the daily peak is predicted up to 7-day lead time using transfer function model for the daily energy. The input variable of this model is the daily average dry bulb temperature which is modeled using a univariate time series method. The load factor used for calculating the daily peak is the perfect (or actual) load factor values.

Model 9: Daily peak load model using energy and weather information (prediction using forecasted weather data) with actual load factor values.

This model is the same as model 8 with the exception that predicted weather values are used in calculating the energy predictions.

Model 10: Daily peak model using enegy data only with average load factor values.

This model is the same as model 7 with the exception that average load factor is used instead of the actual load factor values. The average load factor is based on the most recent historical data that are used in building the energy model.

Model 11: Daily peak load model using energy and weather information (prediction using accurate weather data) with average factor values.

This model is the same as model 8 with the exception that average load factor is used instead of the actual load factor values.

Model 12: Daily peak load model using energy and weather information (prediction using forecasted weather data) with average factor values.

This model is the same as model 9 with the exception that average load factor is used instead of the actual load factor values.

Model 13: Daily peak model using predcited energy and load factor data.

This model is the same as model 7 with the exception that the load factor used is also predicted using load factor information only, i.e. univariate time series model.

Model 14: Daily peak load model using predcited energy and load factor data with weather information (prediction using accurate weather data).

This model is the same as model 8 with the exception that both the daily energy and the load factor are modeled using weather information. Actual weather values are used in the prediction of both the daily energy and the load factor.

Model 15: Daily peak load model using predcited energy and load factor data with weather information (prediction using forecasted weather data).

This model is the same as model 14 with the exception that predicted weather information is used in the prediction of both the daily energy and the load factor.

9.3 Modeling Evaluation

The models that have been presented in the previous section are mainly developed using the time series approach. This technique has been presented in chapter 5 in details. Although the time series approach has been applied in modeling the hourly electrical load for short lead time (up to 24 hour lead time), models for the daily peak and specially models that are developed using the energy method can be considered as new applications to the daily peak load prediction. The energy approach as will be demonstrated next is shown to be more simple and more accurate especially for addressing the one-week lead time forecast.

Results of the simulation prediction of all of these models have been obtained for the months, February, May, August, and October representing Winter, Spring, Summer, and Fall seasons. Some of the models that are developed using both the power and energy methods for this simulation are demonstrated in Appendix D. Results of the daily peak 1-day and 1-week ahead predictions for all of this techniques for all seasons are shown in Tables 44 through 73 in Appendix E. A summary of the absolute error of the daily peak forecast error are shown in Table 20 through Table 23. The following abbreviations are defined.

UV. Univariate time series model

TFA. Transfer Function time series model with accurate future input data

TFF. Transfer Function time series model with predicted future input data

9.3.1 Daily prediction

Inspection of the results of the different developed models gives the following rules or conclusions for the predictions of the daily peak load one day ahead.

- Winter season.

  IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)
  THEN the TFA daily energy model with the obtained LF (i.e., Model 8) gives the best 1-day ahead daily peak prediction.

  IF the future weather variables (mainly the dry bulb temperature) can be known accurately (i.e., through experts or external predictions to the system)
  THEN the TFA daily peak model (i.e., Model 5) gives the best 1-day ahead daily peak prediction.

Table 20. Daily Peak Forecast Error Using Hourly Load Model Predictions

(a) One day lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	199.49	3.08	184.84	3.62	574.41	7.90	226.56	4.24
TFA	250.81	3.79	251.65	4.86	564.66	7.78	218.85	4.14
TFF	276.56	4.24	395.46	7.77	574.36	7.90	235.29	4.44

(b) One week lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	687.90	10.55	851.42	16.61	1822.94	24.74	777.70	14.52
TFA	689.93	10.54	1227.92	23.98	1864.99	25.65	733.45	13.84
TFF	728.13	11.18	2616.06	50.76	2013.30	27.64	1016.82	18.88

Table 21. Daily Peak Forecast Error Using Daily Peak Load Model

(a) One day lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	284.03	4.41	179.71	3.59	641.20	8.88	363.67	7.13
TFA	196.94	3.08	271.98	5.41	398.71	5.34	466.46	9.00
TFF	299.90	4.68	296.25	5.96	947.98	12.24	350.09	6.69

(b) One week lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	540.29	8.33	223.34	4.62	858.15	12.42	747.08	14.67
TFA	223.05	3.40	329.34	6.61	562.32	7.74	723.42	13.85
TFF	436.34	6.75	292.56	6.09	1173.41	16.72	735.73	14.55

Table 22. Daily Peak Forecast Error Using Daily Energy Prediction and Actual Load Factor

(a) One day lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	240.18	3.68	174.77	3.47	486.18	6.83	350.07	6.91
TFA	191.91	2.97	332.69	6.52	175.91	2.40	374.97	7.02
TFF	354.18	5.44	289.61	5.76	508.09	6.61	343.08	6.44

(b) one week lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	514.07	7.97	210.36	4.33	796.00	11.40	652.40	12.87
TFA	191.91	2.97	415.56	8.24	371.71	5.08	562.47	10.44
TFF	532.00	8.27	265.68	5.47	996.53	14.18	471.09	9.13

Table 23. Daily Peak Forecast Error Using Daily Energy Prediction and Average Load Factor

(a) One day lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	281.23	4.34	227.99	4.57	601.95	8.46	409.82	8.10
TFA	228.60	3.56	352.11	6.98	248.70	3.52	365.97	6.89
TFF	367.62	5.65	313.25	6.31	645.73	8.47	361.55	6.80

(b) One week lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	439.77	6.87	248.39	5.15	866.87	12.54	755.83	14.84
TFA	228.60	3.56	442.61	8.86	433.09	6.04	543.67	10.10
TFF	447.83	6.98	311.55	6.43	1077.56	15.47	541.10	10.50

Table 24. Daily Peak Forecast Error Using Daily Energy and Load Factor Predictions

(a) One day lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	281.23	4.34	260.12	5.21	616.45	8.61	365.10	7.16
TFA	239.88	3.75	346.35	6.85	222.35	3.10	357.38	6.70
TFF	371.52	5.72	308.10	6.19	659.58	8.53	353.26	6.62

(b) One week lead time

MODEL	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
UV	439.77	6.87	249.42	5.16	866.87	12.54	739.82	14.54
TFA	239.88	3.75	454.11	9.07	432.71	6.06	551.62	10.20
TFF	447.81	6.98	299.18	6.19	1077.64	15.47	521.90	10.13

IF the future weather variables (mainly the dry bulb temperature) can not be known accurately

THEN the UV hourly load model (i.e., Model 1) gives the best 1-day ahead daily peak prediction.

- Spring season

IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)

THEN the TFA daily energy model with the obtained LF (i.e., Model 8) gives the best 1-day ahead daily peak prediction.

IF the future weather variables (mainly the dry bulb temperature) can not be known accurately (i.e., through experts or external predictions to the system)

THEN the TFA daily energy model with predicted LF by the system using TFA (i.e., Model 14) gives the best 1-day ahead daily peak prediction. A close result can also be obtained with the TFA daily energy model with average load factor (i.e., Model 10).

IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can not be known accurately

THEN the UV daily peak model (i.e., Model 4) gives the best 1-day ahead daily peak prediction.

- Summer season

IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)

THEN the TFA daily energy model with the obtained LF (i.e., Model 8) gives the best 1-day ahead daily peak prediction.

IF the future weather variables (mainly the dry bulb temperature) can be known accurately (i.e., through experts or external predictions to the system)
THEN the TFA daily energy model with the predicted LF using TFA (i.e, Model 14) gives the best 1-day ahead daily peak prediction.

IF the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)
THEN the UV daily energy model with the obtained LF (i.e., Model 7) gives the best 1-day ahead daily peak prediction.

IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can not be known accurately.
THEN the UV daily peak model or the TFF daily peak model (i.e., Model 4 and Model 6) gives the best 1-day ahead daily peak prediction.

- Fall season

IF the future weather variables (mainly the dry bulb temperature) can be known accurately (i.e., through experts or external predictions to the system)
THEN the TFA hourly load model (i.e, Model 2) gives the best 1-day ahead daily peak prediction.

IF the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)
THEN the TFF daily energy model with this LF (i.e, Model 9) gives the best 1-day ahead daily peak prediction.

IF the future load factor, LF, can not be obtained accurately.

THEN the TFF daily peak model (i.e., Model 6) gives the best 1-day ahead daily peak prediction. A closer result can also be obtained using the TFF daily energy with predicted load factor using the TFF modeling approach (i.e., model 15).

9.3.2 Weekly prediction

For the daily peak load seven day ahead predictions the following rules or conclusions are established.

- Winter season.

  IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)
  THEN the TFA daily energy model with the obtained LF (i.e., Model 8) gives the best 7-day ahead daily peak prediction.

  IF the future weather variables (mainly the dry bulb temperature) can be known accurately (i.e., through experts or external predictions to the system)
  THEN the TFA daily peak model (i.e., Model 5) gives the best 7-day ahead daily peak prediction.

  IF the future weather variables (mainly the dry bulb temperature) can not be known accurately
  THEN the UV daily energy model with average load factor, LF, (i.e., Model 10) gives the best 7-day ahead daily peak prediction.

- Spring season

IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)
THEN the TFA daily energy model with the obtained LF (i.e., Model 8) gives the best 7-day ahead daily peak prediction.

IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can not be known accurately (i.e., through experts or external predictions to the system)
THEN the UV daily peak model (i.e., Model 4) gives the best 7-day ahead daily peak prediction.

- Summer season

IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)
THEN the TFA daily energy model with the obtained LF (i.e., Model 8) gives the best 7-day ahead daily peak prediction.

IF the future weather variables (mainly the dry bulb temperature) can be known accurately (i.e., through experts or external predictions to the system)
THEN the TFA daily energy model with the average LF (i.e, Model 11) gives the best 7-day ahead daily peak prediction. A closer model to the this model is the TFA daily energy with LF predicted using also TFA (i.e., Model 14).

IF both the future weather variables (mainly the dry bulb temperature) and the future load factor, LF, can not be known accurately (i.e., through experts or external predictions to the system)

THEN the UV daily energy model with average LF (i.e., Model 10) gives the best 7-day ahead daily peak prediction. A closer model to this is the UV daily energy with predicted LF using also a UV model.

- Fall season

IF the future load factor, LF, can be known accurately (i.e., through experts or external predictions to the system)
THEN the TFF daily energy model with this LF (i.e, Model 9) gives the best 7-day ahead daily peak prediction.

IF the future load factor, LF, can not be known accurately
THEN the TFF daily energy model with predicted LF using TFF model (i.e, Model 15) gives the best 7-day ahead daily peak prediction.

9.4 Adaptive Weekly Predictions

Adaptive knowledge-based load forecasting models were developed for the one-week ahead daily peak load predictions under the knowledge-based load forecasting system using two parallel approaches. In the first approach expert information was used to produce a weighted average model using different statistical models. The second approach was based totally on rules derived from the electric utility experts, and was free of any significant statistical computation.

9.4.1 Statistical modeling

The relationship between load (MW), weather variables, time of day, day types and seasons can be obtained from load forecast domain experts. These relationships, and hourly historical loads and weather data were then selectively used for various statistical techniques (e.g., univariate, transfer function and linear regression). Among the models that are presented in section 9.2.1 and 9.2.2 the models in winter and summer seasons was concluded to be highly dependent on weather conditions. It was also concluded that the hourly load models were not suitable for weekly load predictions. It also has been demonstrated in chapter 7 that regression models to produce good prediction provided that accurate future weather variable are provided. Models using the power and energy methods were developed using the linear regression technique.

The following statistical techniques were applied to the one week daily load predictions. The models with input variables assumed available accurate future information. These Techniques are as follows.

- Univariate (UV) Models;
- Transfer function (TFA) Models; and
- Regression (LR) Models.

Discussion about the models using the UV and the TF techniques has been presented in section 9.2.1 and section 9.2.2. For the LR models the following models were developed:

Model 16: Daily peak load model using daily peak load with accurate weather information.

This model is developed using the daily peak load data and accurate dry bulb and dew point temperature weather variables. The weather variables are assumed to be available either through experts or predicted accurately external to the load forecasting system.

Model 17: Daily peak load model using daily energy prediction with accurate weather information and average load factor.

This model is developed using the daily energy data and accurate dry bulb and dew point temperature weather variables. The weather variables are assumed to be available either through experts or predicted accurately external to the load forecasting system. The daily peak is obtained from the predicted daily energy and the average load factor, LF. The average load factor is obtained by using the historical data for several similar day types (Mondays, Tuesdays, etc.) in the season. Note that this average LF is different from the average LF factor used in the models 10 to 12 which is obtained by simply average the previous month daily load factors.

Model 18: Daily peak load model using daily energy prediction with accurate weather information and accurate load factor.

This model is developed using the daily energy data and accurate dry bulb and dew point temperature weather variables. The weather variables are assumed to be available either through experts or predicted accurately external to the load forecasting system. The daily peak is obtained from the predicted daily energy and the LF as obtained from experts or predicted accurately external to the load forecasting system.

Samples showing how some of these models were developed are given in Appendix D.

9.4.2 Weighted Averaging

It was observed as demonstrated by the prediction results of the models presented in section 9.2.1 and section 9.2.2 in Appendix E that different statistical techniques and models performed differently on different days in different seasons. A weighted average load forecast was then used which judiciously combined forecasts from these three techniques (i.e, UV, TFA, and LR). The weights were based on the performance of various techniques under different weather conditions, and the sensitivity of load to weather. Analysis of the statistical techniques and discussions with electric utility system operators resulted in the weights shown in Table 25.

These weights may change from one month to another depending on variations in weather.

9.4.3 Rule-based modeling

This modeling approach was centered around rules that are derived from electric utility experts. This rule based forecast model consisted of a "reference load" and a multiplicative correction factors. In some circumstances additive correction factors were needed to rectify the load forecasts. The model for predicting the 168-hour lead time load forecast and the 1-week lead time daily peak forecasts has been presented in chapter 6 for the summer season with detailed discussion. Results of this modeling approach for the one week daily peak forecasts in presented in the next section.

9.5 Results

Results obtained by applying the knowledge base to the statistical and rule-based techniques are discussed in the following. Historical load patterns and weather information in the service area of a major electric utility in Virginia was used for the results presented in this work.

Table 25. Weighted Averaging Values for the Statistical Models

Month	Univariate Weight %	Transfer Fn. Weight %	Regression Weight %
Febraury	10.0	55.0	35.0
August	15.0	35.0	50.0

9.5.1 *Statistical modeling*

The statistical modeling techniques presented in section 9.4.1 (i.e., UV, TFA, and LR) have been applied to the three best load models presented in earlier sections. These load models are as follows:

Model I: Daily peak load

This includes the models 4, 5, and 16 developed using UV, TFA, and LR techniques respectively.

Model II: Daily energy and average load factor

This includes the models 10, 11, and 17 developed using UV, TFA, and LR techniques respectively.

Model III: Daily energy and actual load factor

This includes the models 7, 8, and 18 developed using UV, TFA, and LR techniques respectively.

Results that were obtained by using the statistical techniques are presented in Tables 26 through 31. For all cases the model parameters were estimated using January and July data for February and August forecasts respectively. The MW and per cent numbers represent the difference between the actual and forecast loads for all days of that particular month. In these tables the percentage error is the error with respect to the daily peak load. The numbers presented at the bottom are the absolute averages for all days of the month.

As the univariate model used only the load (MW) variable the errors are small only under stable conditions. Major changes in load caused by significant variations in weather could not be captured by this model. On the other hand the model performance was not subject to the errors in the weather forecast because this information was not used. As the weather was generally stable (i.e., no significant variations in temperature) in February the average forecast errors for the month ranged between 6% and 8% for the three models.

The situation was, however, different in August when there were significant temperature variations. The daytime temperature dropped by more than 25°F from the first to the second weekend. The univariate model was obviously unable to capture the effects of these large temperature variations causing high errors in the forecast during the 13th through the 16th of the month (see Table 27). The energy models (Model 17,18) generally gave better forecast than the peak load model (Model 16).

The transfer function model used both load and weather variables to generate the forecast. Results presented in Tables 28 and 29 were obtained by using accurate weather conditions in February and August respectively. Transfer function based models also performed better under stable weather conditions. As it used weather information the transfer function based forecasts for February (as shown in Table 28) were significantly better than those obtained from the univariate model (see Table 26) for the same month. On the other hand, due to drastic changes in the weather pattern in August the errors (see Table 29) were higher in this month than in February for the transfer function model. These errors, however, were still lower than those seen for August univariate models.

The third case refers to the use of the linear regression model. This model also used the load and weather information. Forecast errors for February (see Table 30) were somewhat higher than what were seen for the transfer function models (see Table 28). This suggested that, under stable weather conditions, the more sensitive transfer function model performed better than the regression model. On the other hand, when weather conditions became unstable in August the regression model performed better (see Table 31) than the transfer function model. (See Table 29).

In order to present a comprehensive error analysis, percentage errors for all techniques and models are shown in Table 32. It is seen from this table that model 3 using the energy forecast and the actual load factor gave the best overall forecast. The forecast error obtained by using the energy forecast and the average load factor (model 17) was also comparable. In summary, the transfer function technique worked better under stable weather conditions in

Table 26. Forecast Errors for February Using Univariate Models

DAY	Model 4		Model 10		Model 7	
	MW	%	MW	%	MW	%
1	363.71	5.55	-69.82	-1.06	-273.89	-4.18
2	-541.50	-9.00	-701.52	-11.66	-634.41	-10.54
3	-197.49	-3.20	-533.43	-8.64	-826.10	-13.39
4	172.35	2.52	-16.89	-.25	95.15	1.39
5	317.18	4.88	89.69	1.38	224.69	3.45
6	833.62	12.89	440.35	6.81	398.97	6.17
7	472.56	6.84	473.71	6.86	575.64	8.34
8	508.01	7.15	599.49	8.43	595.62	8.38
9	1368.18	18.55	957.75	12.99	812.41	11.02
10	1088.67	14.95	957.87	13.16	973.91	13.38
11	692.34	9.26	675.34	9.03	985.66	13.18
12	65.65	.99	69.62	1.04	415.21	6.23
13	-146.14	-2.24	143.43	2.19	248.16	3.80
14	78.79	1.12	233.79	3.33	470.01	6.70
15	-354.63	-5.26	-80.75	-1.20	-157.94	-2.34
16	-801.53	-12.06	-202.52	-3.05	-389.29	-5.86
17	-949.34	-14.88	-480.65	-7.53	-385.00	-6.03
18	-859.13	-13.13	-663.98	-10.15	-750.55	-11.47
19	-929.67	-16.17	-1046.10	-18.19	-973.11	-16.92
20	-1104.60	-20.22	-1072.54	-19.63	-1064.99	-19.49
21	-697.75	-11.18	-666.66	-10.68	-857.62	-13.74
22	-470.44	-7.62	-510.09	-8.26	-852.22	-13.80
23	-548.26	-9.20	-635.34	-10.66	-660.69	-11.09
24	45.65	.72	-254.41	-4.03	-291.56	-4.62
25	172.06	2.62	-110.33	-1.68	36.78	.56
26	536.80	8.50	29.08	.46	114.77	1.82
27	241.13	4.18	-277.03	-4.80	-196.30	-3.40
28	570.99	8.45	340.05	5.03	133.42	1.97
Aver.	540.29	8.33	440.45	6.86	514.07	7.97

Table 27. Forecast Errors for August Using Univariate Models

DAY	Model 4		Model 10		Model 7	
	MW	%	MW	%	MW	%
1	731.53	8.97	741.18	9.08	916.94	11.24
2	772.11	9.40	736.36	8.96	784.23	9.55
3	654.11	8.00	602.94	7.37	768.01	9.39
4	653.51	7.95	728.00	8.86	603.71	7.34
5	644.50	7.86	676.01	8.24	528.77	6.45
6	66.27	.87	128.59	1.69	67.58	.89
7	-111.07	-1.49	22.80	.31	-79.99	-1.07
8	1087.95	12.46	998.23	11.43	876.46	10.04
9	1116.75	12.73	999.06	11.39	959.47	10.94
10	309.96	3.89	132.45	1.66	266.13	3.34
11	1261.20	14.14	1281.83	14.37	974.14	10.92
12	-737.59	-10.66	-726.01	-10.50	-453.13	-6.55
13	-2497.44	-49.68	-2483.06	-49.39	-1930.67	-38.41
14	-2847.94	-61.42	-2727.50	-58.82	-2332.91	-50.31
15	-1979.20	-34.17	-2013.88	-34.77	-1742.61	-30.09
16	-1479.29	-23.48	-1611.87	-25.58	-1456.11	-23.11
17	-308.44	-4.23	-455.51	-6.25	-532.89	-7.31
18	-95.69	-1.24	-66.56	-.86	7.96	.10
19	1129.78	13.29	1118.90	13.17	1043.09	12.27
20	1782.95	20.42	1863.65	21.34	1557.70	17.84
21	659.49	8.77	892.27	11.86	914.03	12.15
22	2285.19	24.30	2379.06	25.30	1853.57	19.71
23	708.25	8.92	719.51	9.06	1079.55	13.60
24	-85.44	-1.16	-116.54	-1.58	142.44	1.93
25	-473.97	-6.70	-476.22	-6.73	-520.63	-7.36
26	-699.27	-9.96	-732.45	-10.43	-818.94	-11.67
27	-219.20	-2.90	-198.93	-2.63	-618.21	-8.19
28	-498.70	-7.12	-422.92	-6.04	-483.21	-6.90
29	-39.31	-.50	29.03	.37	57.53	.73
30	499.55	6.17	293.95	3.63	173.54	2.14
31	166.92	2.19	28.79	.38	131.85	1.73
Aver.	858.15	12.42	851.74	12.32	796.00	11.40

Table 28. Forecast Error for February Using Transfer Function Models

DAY	Model 5		Model 11		Model 8	
	MW	%	MW	%	MW	%
1	373.76	5.70	22.87	.35	-178.35	-2.72
2	45.74	.76	121.28	2.02	180.17	2.99
3	217.09	3.52	609.62	9.88	366.85	5.94
4	126.21	1.85	255.05	3.73	362.64	5.31
5	-5.16	-.08	23.75	.37	160.15	2.46
6	129.57	2.00	212.15	3.28	169.20	2.62
7	312.82	4.53	53.74	.78	162.32	2.35
8	435.88	6.13	308.58	4.34	304.53	4.28
9	639.89	8.68	70.52	.96	-94.92	-1.29
10	402.11	5.52	-259.64	-3.57	-240.51	-3.30
11	398.19	5.32	-460.18	-6.15	-98.08	-1.31
12	70.01	1.05	-454.38	-6.82	-81.33	-1.22
13	24.83	.38	-208.76	-3.19	-98.27	-1.50
14	117.61	1.68	-119.59	-1.71	128.94	1.84
15	186.52	2.77	-109.15	-1.62	-186.66	-2.77
16	-159.78	-2.40	7.33	.11	-173.72	-2.61
17	-316.66	-4.96	-170.31	-2.67	-78.98	-1.24
18	-61.68	-.94	-247.89	-3.79	-329.45	-5.04
19	-300.94	-5.23	-242.60	-4.22	-178.24	-3.10
20	-520.70	-9.53	-315.44	-5.77	-308.77	-5.65
21	147.75	2.37	-279.37	-4.47	-459.63	-7.36
22	231.28	3.74	297.28	4.81	-3.55	-.06
23	-360.49	-6.05	298.19	5.00	276.42	4.64
24	10.62	.17	180.42	2.86	145.74	2.31
25	-99.81	-1.52	-34.83	-.53	110.62	1.69
26	111.38	1.76	97.77	1.55	182.52	2.89
27	19.78	.34	-99.26	-1.72	-20.89	-.36
28	419.27	6.20	493.72	7.30	292.04	4.32
Aver.	223.05	3.40	216.20	3.34	191.91	2.97

Table 29. Forecast Error for August Using Transfer Function Models

DAY	Model 5		Model 11		Model 8	
	MW	%	MW	%	MW	%
1	-317.11	-3.89	166.57	2.04	355.95	4.36
2	676.29	8.23	544.26	6.63	593.35	7.22
3	553.47	6.77	428.32	5.24	597.20	7.30
4	829.41	10.09	790.39	9.61	667.13	8.11
5	386.69	4.71	635.02	7.74	486.98	5.94
6	356.43	4.68	218.81	2.87	158.53	2.08
7	273.00	3.67	265.84	3.57	166.42	2.24
8	875.04	10.02	487.26	5.58	357.46	4.09
9	-170.91	-1.95	179.93	2.05	136.17	1.55
10	337.92	4.25	9.92	.12	145.70	1.83
11	-341.68	-3.83	266.60	2.99	-82.00	-.92
12	-160.68	-2.32	-429.43	-6.21	-167.14	-2.42
13	-267.98	-5.33	-731.39	-14.55	-307.84	-6.12
14	-950.42	-20.50	-913.50	-19.70	-616.11	-13.29
15	-1379.18	-23.81	-927.45	-16.01	-693.93	-11.98
16	-814.74	-12.93	-671.39	-10.66	-534.15	-8.48
17	-846.26	-11.61	-397.85	-5.46	-474.66	-6.51
18	-291.11	-3.77	-397.69	-5.15	-319.99	-4.15
19	561.11	6.60	362.75	4.27	279.18	3.29
20	-151.64	-1.74	595.45	6.82	233.01	2.67
21	987.01	13.12	566.94	7.54	589.77	7.84
22	1055.84	11.23	1400.84	14.90	802.17	8.53
23	1509.48	19.01	579.72	7.30	946.73	11.92
24	888.58	12.06	246.03	3.34	492.46	6.69
25	385.80	5.46	319.60	4.52	279.87	3.96
26	-779.55	-11.10	-139.53	-1.99	-219.41	-3.13
27	-224.18	-2.97	133.97	1.77	-267.30	-3.54
28	-449.40	-6.42	-112.13	-1.60	-169.90	-2.43
29	121.41	1.54	-96.14	-1.22	-67.18	-.85
30	-95.05	-1.17	-65.38	-.81	-191.33	-2.36
31	-394.69	-5.17	20.73	.27	123.89	1.62
Aver	562.32	7.74	422.61	5.89	371.71	5.08

Table 30. Forecast Error for February Using Regression Models

DAY	Model 16		Model 17		Model 18	
	MW	%	MW	%	MW	%
1	114.65	1.75	151.00	2.30	-46.27	-.71
2	70.35	1.17	919.45	15.28	970.37	16.12
3	-83.40	-1.35	804.71	13.04	570.46	9.24
4	-64.05	-.94	-82.38	-1.21	30.73	.45
5	-303.02	-4.66	-351.87	-5.41	-207.57	-3.19
6	-752.07	-11.63	-51.53	-.80	-96.29	-1.49
7	228.44	3.31	304.28	4.41	408.89	5.92
8	290.82	4.09	387.25	5.45	383.24	5.39
9	296.75	4.02	48.15	.65	-117.80	-1.60
10	6.83	.09	105.08	1.44	123.29	1.69
11	-819.38	-10.95	-185.06	-2.47	164.49	2.20
12	-758.29	-11.38	-659.39	-9.90	-275.59	-4.14
13	-1042.93	-15.95	-469.24	-7.18	-354.48	-5.42
14	194.71	2.78	91.97	1.31	333.13	4.75
15	7.36	.11	188.19	2.79	114.04	1.69
16	47.04	.71	139.62	2.10	-37.82	-.57
17	-13.77	-.22	-51.97	-.81	37.71	.59
18	167.29	2.56	-49.63	-.76	-128.82	-1.97
19	-1108.07	-19.27	-466.99	-8.12	-400.22	-6.96
20	-1274.68	-23.33	-582.27	-10.66	-575.29	-10.53
21	-400.50	-6.42	-91.89	-1.47	-266.98	-4.28
22	-57.61	-.93	725.94	11.75	447.04	7.24
23	-272.83	-4.58	495.52	8.32	474.51	7.96
24	-58.57	-.93	117.98	1.87	82.94	1.31
25	-192.74	-2.94	5.90	.09	150.45	2.29
26	275.04	4.35	-106.37	-1.68	-18.84	-.30
27	-454.92	-7.88	-256.55	-4.44	-176.08	-3.05
28	119.01	1.76	737.42	10.91	543.58	8.04
Aver.	338.40	5.36	308.13	4.88	269.18	4.25

Table 31. Forecast Error for August Using Regression Models

DAY	Model 16		Model 17		Model 18	
	MW	%	MW	%	MW	%
1	-381.51	-4.68	-182.27	-2.23	15.37	.19
2	-119.92	-1.46	-39.42	-.48	13.42	.16
3	-286.69	-3.51	-187.78	-2.30	-5.47	-.07
4	93.12	1.13	168.87	2.05	35.31	.43
5	-275.24	-3.36	147.67	1.80	-9.90	-.12
6	384.34	5.04	-169.14	-2.22	-232.57	-3.05
7	33.49	.45	-108.67	-1.46	-213.28	-2.87
8	138.22	1.58	405.04	4.64	273.94	3.14
9	-95.07	-1.08	225.34	2.57	181.81	2.07
10	132.40	1.66	-11.05	-.14	125.08	1.57
11	-75.55	-.85	389.12	4.36	45.45	.51
12	56.45	.82	-492.63	-7.12	-228.08	-3.30
13	-1941.45	-38.62	-757.72	-15.07	-332.23	-6.61
14	-1552.78	-33.49	-574.15	-12.38	-294.94	-6.36
15	246.67	4.26	-351.98	-6.08	-138.46	-2.39
16	-228.61	-3.63	-300.39	-4.77	-170.45	-2.71
17	-329.75	-4.52	-211.18	-2.90	-286.12	-3.92
18	-564.17	-7.31	-198.61	-2.57	-122.82	-1.59
19	32.94	.39	-31.27	-.37	-118.89	-1.40
20	328.12	3.76	17.68	.20	-370.50	-4.24
21	-593.26	-7.89	-286.71	-3.81	-261.07	-3.47
22	405.45	4.31	700.82	7.45	49.79	.53
23	309.35	3.90	-391.34	-4.93	24.08	.30
24	210.90	2.86	-275.69	-3.74	-11.20	-.15
25	242.75	3.43	292.13	4.13	252.24	3.57
26	-21.82	-.31	142.51	2.03	65.78	.94
27	127.57	1.69	326.42	4.32	-64.44	-.85
28	-580.08	-8.28	-638.88	-9.12	-700.92	-10.01
29	-141.14	-1.79	-162.76	-2.07	-133.56	-1.69
30	302.77	3.74	4.35	.05	-120.52	-1.49
31	-174.56	-2.29	-239.51	-3.14	-132.82	-1.74
Aver.	335.68	5.23	271.97	3.89	162.27	2.30

February, but the regression technique had a comparatively better performance under unstable weather conditions in August.

When forecasts for the three models were averaged according to the weighting factors presented in section 9.4.2 the model performance was more robust as shown in Tables 33 and 34.

9.5.2 *Rule-based modeling*

Finally the rule-base presented in section 9.4.4 was applied to generate forecasts which did not depend on statistical techniques. It was pointed out by system operators in electric utilities that effect of weather on the load might manifest differently based on some inertia effects. In order to show these effects the load forecasting algorithm used both the temperature at the hour of the forecast, and the average temperatures over the 12 and 24 hours prior to the forecast hour.

Results from the rule-based load forecasting model for August are presented on Table 35. It appears that when the 24-hour average temperatures prior to the forecast hour was used as one of the variables, the forecast error was the least. The 2.79% average error for the month was somewhat higher than the 2.30% average error obtained using the linear regression technique (see Table 31). However, the largest single error for the rule-based technique was 6.44%, whereas that for the linear regression technique was 10.01%. The rule-based technique was, therefore, more robust.

9.6 Conclusions

The performance of the intelligent load forecasting system presented in chapter 8 is evaluated in this chapter. Along the application of the new approach of combining both the

Table 32. Percentage Errors for Various Techniques and Models

DAY	Model I		Model II		Model III	
	Feb	Aug	Feb	Aug	Feb	Aug
Univariate	8.33	12.42	6.86	12.32	7.97	11.40
Trans. Fn.	3.40	7.74	3.34	5.89	2.97	5.08
Regression	5.36	5.23	4.88	3.89	4.25	2.30

Table 33. Forecast Error for February Using Weighted UV, TF, and LR Models

DAY	Model I		Model II		Model III	
	MW	%	MW	%	MW	%
1	282.07	4.30	58.45	.89	-141.68	-2.16
2	-4.37	-.07	318.36	5.29	375.28	6.23
3	70.46	1.14	563.60	9.13	318.82	5.16
4	64.23	.94	109.76	1.60	219.72	3.22
5	-77.18	-1.19	-101.12	-1.55	37.90	.58
6	-108.60	-1.68	142.68	2.20	99.26	1.54
7	299.26	4.33	183.43	2.66	289.95	4.20
8	392.32	5.52	365.21	5.14	361.19	5.08
9	592.62	8.04	151.41	2.05	-12.20	-.17
10	332.42	4.56	-10.24	-.14	8.26	.11
11	1.46	.02	-250.34	-3.34	102.19	1.37
12	-220.33	-3.31	-473.73	-7.11	-99.67	-1.50
13	-365.98	-5.60	-264.71	-4.05	-153.30	-2.34
14	140.71	2.01	-10.21	-.15	234.51	3.34
15	69.70	1.04	-2.24	-.03	-78.54	-1.17
16	-151.57	-2.28	32.65	.49	-147.71	-2.22
17	-273.92	-4.29	-159.93	-2.51	-68.74	-1.08
18	-61.29	-.93	-220.11	-3.37	-301.34	-4.61
19	-646.31	-11.24	-401.49	-6.98	-335.42	-5.83
20	-842.98	-15.43	-484.54	-8.87	-477.67	-8.74
21	-128.69	-2.06	-252.48	-4.04	-432.00	-6.92
22	60.00	.97	366.57	5.93	69.29	1.12
23	-348.59	-5.85	273.90	4.60	252.04	4.23
24	-10.09	-.16	115.08	1.82	80.03	1.27
25	-105.15	-1.60	-28.12	-.43	117.18	1.79
26	211.20	3.34	19.45	.31	105.27	1.67
27	-124.23	-2.15	-172.09	-2.98	-92.75	-1.61
28	329.35	4.87	563.65	8.34	364.22	5.39
Aver.	225.54	3.53	217.70	3.43	192.00	3.02

Table 34. Forecast Error for August Using Weighted UV, TF, and LR Models

DAY	Model I		Model II		Model III	
	MW	%	MW	%	MW	%
1	-192.01	-2.36	78.34	.96	269.81	3.31
2	292.56	3.56	281.24	3.42	332.02	4.04
3	148.49	1.81	146.46	1.79	321.49	3.93
4	434.88	5.29	470.27	5.72	341.71	4.15
5	94.40	1.15	397.49	4.84	244.81	2.99
6	326.86	4.29	11.30	.15	-50.66	-.66
7	95.63	1.29	42.13	.57	-60.39	-.81
8	538.57	6.17	522.80	5.99	393.55	4.51
9	60.16	.69	325.50	3.71	282.48	3.22
10	230.97	2.90	17.81	.22	153.45	1.93
11	31.82	.36	480.14	5.38	140.15	1.57
12	-138.65	-2.00	-505.52	-7.31	-240.51	-3.48
13	-1439.13	-28.63	-1007.31	-20.04	-563.46	-11.21
14	-1536.23	-33.13	-1015.93	-21.91	-713.04	-15.38
15	-656.26	-11.33	-802.68	-13.86	-573.50	-9.90
16	-621.36	-9.86	-626.96	-9.95	-490.59	-7.79
17	-507.33	-6.96	-313.16	-4.30	-389.12	-5.34
18	-398.33	-5.16	-248.48	-3.22	-172.21	-2.23
19	382.33	4.50	279.16	3.29	194.73	2.29
20	378.43	4.33	496.80	5.69	129.96	1.49
21	147.75	1.96	188.91	2.51	212.99	2.83
22	915.05	9.73	1197.56	12.73	583.69	6.21
23	789.23	9.94	115.16	1.45	505.33	6.36
24	403.64	5.48	-69.22	-.94	188.13	2.56
25	185.31	2.62	186.49	2.64	145.98	2.07
26	-388.64	-5.53	-87.45	-1.25	-166.74	-2.38
27	-47.56	-.63	180.26	2.38	-218.51	-2.89
28	-522.14	-7.45	-422.12	-6.03	-482.41	-6.89
29	-33.97	-.43	-110.67	-1.41	-81.66	-1.03
30	193.05	2.39	23.38	.29	-101.19	-1.25
31	-200.38	-2.63	-108.18	-1.42	-3.27	-.04
Aver.	397.78	5.95	347.06	5.01	282.18	4.02

Table 35. Forecast Error for August Using the Expert System Model

Day	12 HOUR LAG		24 HOUR LAG	
	MW	%	MW	%
1	-142.82	-1.75	-61.64	-.76
2	181.21	2.21	164.96	2.01
3	-149.58	-1.83	-180.60	-2.21
4	177.38	2.16	184.21	2.24
5	-211.42	-2.58	-120.43	-1.47
6	177.75	2.33	202.19	2.65
7	183.11	2.46	132.62	1.78
8	277.16	3.17	413.07	4.73
9	269.42	3.07	261.98	2.99
10	286.77	3.60	139.35	1.75
11	-287.99	-3.23	-147.37	-1.65
12	-182.49	-2.64	-289.70	-4.19
13	155.95	3.10	56.08	1.12
14	-34.02	-.73	-35.42	-.76
15	-469.91	-8.11	-245.18	-4.23
16	-365.73	-5.80	-310.83	-4.93
17	-392.46	-5.38	-233.49	-3.20
18	-484.45	-6.28	-496.65	-6.44
19	362.93	4.27	387.72	4.56
20	11.35	.13	208.09	2.38
21	716.92	9.53	462.11	6.14
22	13.11	.14	254.43	2.71
23	220.46	2.78	31.61	.40
24	219.05	2.97	178.02	2.42
25	303.99	4.30	262.10	3.71
26	-12.82	-.18	73.03	1.04
27	29.23	.39	197.96	2.62
28	-104.85	-1.50	-45.09	-.64
29	-161.08	-2.04	-256.64	-3.26
30	428.99	5.30	442.05	5.46
31	-161.88	-2.12	-166.27	-2.18
Av	231.49	3.10	214.22	2.79

statistical and rule-based approaches, new applications of statistical approaches are also implemented at the same time. This includes the use of energy method for predicting the daily peak load and an intelligent application to the daily hourly load prediction of regression techniques with the use of day intervals and indicator variables.

The application of knowledge base to statistical and rule-based load forecasting techniques is demonstrated. Rules were developed based on long term statistical relationships, and properties identified by system operators in the electric utility industry. These rules and coefficients could be adapted to changing load, weather and load shape conditions by studying the historical data for the previous four weeks only. It is thus shown that fairly simple but accurate statistical models could be developed using only four weeks of historical data, provided some of the relationships governing the electric load and the influential variables are predetermined by experts in the industry. Finally, both the statistical and rule-based techniques which were developed by using rules given by the domain experts provided accurate and robust forecasts. In conclusion it can be said that the knowledge base available from the experts was not only useful in the expert system technique, it could also help in the development of simple but powerful statistical algorithms for load forecasting.

Chapter X

CONCLUSIONS AND RECOMMENDATIONS

An exhaustive study of the application of statistical (conventional) and knowledge-based methods to the load-forecast problem has been presented in this study. This has been a necessary step towards understanding the state of the art of load forecasting, and at the same time discovering the direction in which this research could contribute to the solution of this problem. Through this comprehensive study, it has been found that forecast lead times greater than 24-hour are rarely addressed ever though, such higher lead time forecasts are important to many electric power system operations that have been shown in Figure 1 and discussed in Chapter 3. Also, it has been found that the computation burden is high as a result of using techniques that require heavy calculations and large data bases. And also, most of these algorithms can deal with forecasts under normal operating conditions. If these conditions are altered (such as large variation in the weather conditions, change of power system operations, and actions taken by energy management systems), then forecasts are not adaptable to such new conditions.

The primary focus of this dissertation was the development of a load forecast model for up to one week lead time. A new approach of investigating both the statistical and knowledge based techniques (for this problem) was the core of this dissertation. This approach is pursued in the following:

- Time series methodologies were investigated to predict the hourly load up to 168-hour lead time. Models using the univariate and the transfer function modeling approaches were built to improve the higher lead time accuracy. These include:(1) building models that do not include nonseasonal and daily seasonal moving average parts of the model by introducing equivalent autoregressive parts. (2) Introducing cut off values for the input variables to improve the effect of the transfer function part in the models built. However, the higher lead time forecasts suffered inaccuracy because of the serial built-in error in predictions. From the accuracy results of the application of time series approach to the one-week lead-time prediction it has been concluded that one should seek ways of minimizing the cascading of predictions to improve the weekly prediction accuracy.

- A rule-base approach was then introduced which was purely based on expertise. For this technique data were selected for producing the forecasts that were based on weekly seasonalities. That helped in the construction of the one-week lead time load forecasts from current and previous days grouped on the basis of day types. The forecasts generated using this approach is quite satisfactory and more accurate when compared to those generated using the time series approach. Not only the predictions were more accurate using this approach, but the model structure is also simple and more adaptive to variations in weather conditions.

- Several short term load forecasting models using different statistical techniques were developed. These statistical models, and another model using a rule based approach based on the work of Rahman and Baba [85,106] were applied to daily load predictions. Analysis and evaluation of these models and their predictions were performed using the same data base to understand the characteristics of these models, and hence to find ways of making these models more adaptive to weekly load predictions. Evaluation results confirmed the finding that predictions using the rule-based approach are compatible in the shorter lead time predictions (i.e., daily predictions) to the best statistical modeling approaches (i.e., time series modeling). Results also indicate that the structure of regression model is more appropriate to weekly load predictions. This appropriateness comes from the fact that predictions are minimally affected by previous shorter time predictions. However, regression models are more sensitive to weather variables and consequently requires accurate predictions of the future explanatory variables. The introduction of day time interval in the regression models and day type (i.e., weekday or weekend) helped to account for different weather variables in these varying time frames and consequently improved the accuracy of this modeling technique. Also, the introduction of the indicator variables was proved to improve the performance of the regression models substantially which made regression models more attractive to weekly load predictions.

- An intelligent load forecasting system was introduced. This system is an application of knowledge-based techniques. This knowledge-based technique could be applied to any or both of the statistical and knowledge-based approaches. Rules for selecting the appropriate models for different seasons and lead times were established.

- A new modeling approach for predicting the daily peak by using the daily energy and the the daily load factor was introduced. The models developed for the daily energy includes time series approaches, univariate (UV) and transfer function (TF), and multiple linear regression. Models developed for the load factor includes UV and TF time series models, all day and day type load factor averaging, and load factors as obtained from experts. Accurate results for the weekly daily peak predictions was shown to be in this modeling approach.

- A method of weighting different model predictions to produce a weighted average prediction was presented. The rules for selecting the models to be weighed and their weights were obtained from load forecast domain experts. This method gave more robust prediction results regarding the variability in weighted averaged predictions than the individual predictions of each model separately.

10.1 Recommendations.

The load forecasting models and techniques discussed in this dissertation were implemented off-line. It is desirable that these models and techniques be implemented on-line to make them more valuable. This is especially true for the (knowledge-based) load forecasting system introduced here. Such an implementation requires the availability of more resources, data, experience and time. Therefore, more research are recommended in the following:

- Implementing the (knowledge-based) load forecasting system in an on-line application mode using a high level language as C or an artificial intelligence language such as PROLOG.

- Developing the interface necessary between the knowledge-based expert system language, PROLOG, and the conventional language, FORTRAN or PASCAL, and possibly a communication language such C language that will enable the collection and the transfer of data from other sources.

- Developing an operational environment that will enable altering the data base used for identifying and estimating the set of functions that will be used in issuing the forecasts and also the capability of issuing forecasts under altered future conditions. This also includes the effect of load management on the load forecast.

- Developing an accurate medium-term load forecast for the daily peak load (one to several weeks) using any or both of the previously mentioned approaches or any other technique proved suitable for such lead times.

REFERENCES

1. D. W. Bunn, "Short-Term Load Forecasting: A Review of Procedures in the Electric Supply Industry," J. Opl. Res. Soc., Vol. 33, 1982, pp. 533-545.

2. S. Rahman and R. Bhatnagar, "An Expert System Based Algorithm for Short Term Load Forecast," IEEE Transaction on Power Systems, Vol. 3, No. 2, pp. 392-399, 1988.

3. K. Jabbour, J. F. V. Riveros, D. Landsbergen and W. Meyer, "ALFA: Automated Load Forecasting Assistant," IEEE Transaction on Power Systems, Vol. 3, No. 3, pp. 902-914,

4. R. Bhatnagar and S. Rahman, "Application of Knowledge Based Algorithms in Electric Utility Load Forecasting," IEEE Southeastern Conference, Richmond, Virginia, March 1986.

5. IEEE Committee Report, "Load Forecast Bibliography, Phase I," IEEE Trans. Power App. Syst., vol. PAS-99, No. 1, pp. 53-58, 1980.

6. IEEE Committee Report, "Load Forecast Bibliography, Phase II," IEEE Trans. Power App. Syst., Vol. PAS-100, No. 7, pp. 3217-3220, 1981.

7. G. Gross and F. D. Galiana, "Short Term Load Forecasting," Proc. IEEE, Vol. 75, No. 12, pp. 1558-1973, Dec. 1987.

8. D. W. Bunn and and E. D. Farmer, "Comparative Models for Electrical Load Forecasting," John Wiley & Sons Ltd., 1985.

9. R. Fildes, "Quantitative Forecasting--The State of the Art: Explorative Models," J. Opl. Res. Soc., Vol. 30, No. 8, 1979, pp. 691-710.

10. P. D. Matthewman and H. Nicholson, "Techniques for Load Prediction in the Electricity-Supply Industry," Proc. IEEE, Vol. 115, No. 10, October 1968, pp. 1451-1457.

11. M. A. Abu-El-Magd and N. K. Sinha, "Short-term Load Demand Modeling and Forecasting; A Review," IEEE Transaction on System, Man, and Cybernetics, Vol. SMC-12, No. 3, pp. 370-382, May/June 1982.

12. Engle and Goodrich, "Forecasting Electricity Sales Over the Short-Term: A Comparison of New Methodologies," Electric Power Research Institute, Report No. EM-4772, 1986.

13. W. G. Sullivan and W. W. Claycombe, "Fundamentals of Forecasting," Reston Publishing Company, Inc., 1977.

14. R. G. Brown, "Smoothing, Forecasting and Prediction of Discrete Time Series," Prentice-Hall, Inc., 1962.

15. M. Davies, "The Relationship Between Weather and Electricity Demand," Proc. IEE, Vol. 106, part C, No. 9, pp. 27-37, March 1959.

16. G. T. Heinemann, D. A. Nordman and E. C. Plant, "The Relationship Between Summer Weather and Summer Loads--A Regression Analysis," Trans. IEEE, Vol. PAS-85, No. 11, pp. 1144-1154, November 1966.

17. S. L. Corpening, N. D. Heppen and R. J. Ringlee, "Experience with Weather Sensitive Load Models for Short and Long-Term Forecasting," Trans. IEEE, Vol. PAS-92, No. 6, pp. 1966-1972, November/December 1973.

18. K. N. Stanton, "Medium-Range Weekly and Seasonal Peak Demand Forecasting by Probability Methods," Trans. IEEE, Vol. PAS-90, No. 5/6, pp. 1183-1189, May/June 1971.

19. K. N. Stanton and P. C. Gupta, "Forecasting Annual or Seasonal Peak Demand in Electric Utility Systems," Trans. IEEE, Vol. PAS-89, No. 5/6, pp. 951-959, May/June 1970.

20. N. Weiner, Extrapolation, Interpolation and Smoothing of Stationary Time Series. New York: Wiley, 1949.

21. P. Whittle, Prediction and Regulation by Linear Least Square Methods. London: English Univ., 1963.

22. G. E. P. Box and G. M. Jenkins, Time Series Analysis--Forecasting and Control. Holden-Day, 1970.

23. K. N. Stanton, P. C. Gupta, and A. H. El-Abiad, "Long Range Demand Forecasting for Electric Utility Industry," Proc. PICA Conf., 1969.

24. P. C. Gupta, "A Stochastic Approach to Peak Power Demand Forecasting in Electrical Utility Systems," IEEE Trans. Power App. Syst., Vol. PAS-90, pp. 824-832, 1971.

25. A. Keyhani and A. El-Abiad, "One-Step-Ahead Load Forecasting for on-line Applications," IEEE Winter Power Meeting, Jan. 1975, Paper no. C75 027-8.

26. A. Keyhani, A. El-Abiad, and E. G. Lansing, "Dynamic System Load Generation Control, Using Variable Pressure Steam Generators," IEEE Summer Power Meeting, July 1975, paper no. A75 590-0.

27. R. L. Kashyap and A. R. Rao, "Real Time Recursive Prediction of River Flows," automatica, Vol. 9, pp. 175-183, 1973.

28. A. Keyhani and T. Eliassi Rad, "A Simulation Study for Recursive Prediction of Hourly Load Demands," Proc. PICA Conf., 1977, pp. 228-236.

29. M. Hagan and R. Klein, "Identification Techniques of Box and Jenkins, applied to the Problem of Short-Term Load Forecasting," IEEE Summer Power Meeting, July 1977, paper no. A77 618-2.

30. M. Hagan and R. Klein, "Off-Line and Adaptive Box and Jenkins Models for Load Forecasting," Proc. Lawrence Sump. Syst. and Decision Sci., Berkeley, CA, Oct. 1977.

31. D. W. Marquardt, "An Algorithm for Least Squares Estimation on Non-Linear Parameters," J. Soc. Ind. Appl. Math., Vol. 11, p. 431, 1963.

32. M. Hagan and R. Klein, "On-Line Maximum Likelihood Estimation for Load Forecasting," IEEE Trans. Syst., Man. Cybern., Vol. SMC-8, No. 9, pp. 711-715, 1978.

33. J. Gertler and C. S. Banyasz, "A Recursive (on-line) Maximum Likelihood Identification Method," IEEE Trans. Automat. Contr., Vol. AC-19, pp. 816-820, 1974.

34. M. T. Hagan and S. M. Behr, "The Time Series Approach to Short-Term Load Forecasting," IEEE/PES 1987 Winter Meeting, New Orleans, LA, paper no. 87 WM 044-1.

35. S. Vemuri, E. F. Hill, and R. Balasubramanian, "Load Forecasting Using Stochastic Models," Proc. PICA Conf., 1973, paper no. TAI-A, pp. 31-37.

36. S. Vemuri, E. F. Hill, and R. Balasubramanian, "The Eventual Forecast Function of the Stochastic Models Used in Forecasting the Power System Peak Demand," Proc. Canadian Conf. Automat. Contr., Fredericton, NB, 1973, paper no. 5.3.

37. D. J. Nelsona nd S. Vemuri, "Automatic Load Forecasting," EPRI EL-1758, RP1355-5, Final Report, March 1981.

38. M. S. Abu-Hussien, M. S. Kandil, M. A. Tantawy, and S. A. Farghal, "An Accurate Model for Short-Term Load Forecasting," Trans. IEEE, Vol. PAS-100, No. 9, pp. 4158-4165, September 1981.

39. H. Akaike, "A New Look at the Stochastic Model Identification," IEEE Trans. Automat. Contr., Vol. AC-19, pp. 716-732, 1974.

40. G. D. Irisarri, S. E. Widergen, and P. D. Yehsakul, "On-Line Load Forecasting for Energy Control Center Application," Trans. IEEE, Vol. PAS-101, January 1982, pp. 71-78.

41. T. N. Goh, S. S. Choi, C. H. Tan, and K. C. Tan, "A Comparative Study of Short-Term Forecasting of Energy and Peak Power Demand," Elect. Power Syst. Res., 5(1982), pp. 63-71.

42. T. N. Goh, and Y. O. Lee, "A New Approach to Statistical Forecasting of Daily Peak Power Demand," Elect. Power Syst. Res., 10(1986), pp. 145-148.

43. K. P. Rajurkar and J. L. Nissen, "Data-Dependent Systems Approach to Short-Term Load Forecasting," IEEE Trans. on Sys., Man, and Cyb., Vol. SMC-15, No. 4, July/August 1985, pp. 532-536.

44. F. Meslier, "New Advances in Short-Term Load Forecasting, Using Box and Jenkins Approach," Proc. IEEE PES Annual Meeting, New York, 1978, paper no. A78 051-5.

45. N. D. Uri, "System Load Forecasts for an Electric Utility, Energy Sources, Vol. 3, No. 314, pp. 313-322, 1978.

46. J. C. Liang and M. G. Strintzis, "The Innovation Approach to Power System Load Forecasting," Proc. Control of Power Syst. Conf. Exposition, Oklahoma City, OK, 1978, pp. 109-113.

47. H. P. Van Meeteren and P. J. M. Van Son, "Short-Term Load Prediction with a Combination of Different Models," Proc. PICA Conf., 1979, pp. 192-197.

48. B. DeMartino, G. Fusco, E. Mariani, E. Randino, and P. Ricci, "A Medium- and Short-Term Load Forecasting Model for Electrical Industry," Proc. PICA Conf., 1979, pp. 186-191.

49. A. Ledollter, "Statistical Methods for Forecasting," John Wiley & Sons, 1983.

50. W. R. Christiaanse, "Short-Term Load Forecasting Using General Exponential Smoothing," Trans. IEEE, Vol. PAS-90, No. 2, pp. 900-910, March/April 1971.

51. D. T. Phi, T. A. Austin, G. J. McAllister, D. Thorne, and W. A. Patterson, "Adaptive Forecasting of Electric Demands in New Brunswick," Proc. Canadian Commun. and Power Conf., Montreal, PQ, Oct. 1978, pp. 200-203.

52. M. J. Settlage, "A Two-Stage Statistical Procedure to Forecast Short-Term Power System Loads," M.S. Thesis, Clemson U., Clemson, S. Carolina.

53. M. S. Sachdev and S. A. Ibrahim, "Short-Term On-Line Load Forecasting," IEEE Summer Power Meeting, July 1972, paper no. C72 454-7.

54. A. Feuer, "Forecasting with Adaptive Gradient Exponential Smoothing," The Bell Syst. Tech. Jour., Vol. 62, No. 8, October 1983, pp. 2561-2579.

55. R. G. Brown, "Introduction to Random Signal Analysis and Kalman Filtering," John Wiley & Sons, Inc., 1983.

56. R. E. Kalman, "A New Approach to Linear Filtering and Prediction Problems," Trans. ASME, Journal of Basic Engineering, Vol. 82, Sec. D, pp. 35-45, March 1960.

57. R. E. Kalman, and R. S. Bucy, "A New Approach to Linear Filtering and Prediction Problems," Trans. ASME, Journal of Basic Engineering, Vol. 83, Sec. D, pp. 95-108, March 1961.

58. J. Toyoda, M. Chen, and Y. Inone, "An Application of State Estimation to Short-Term Load Forecasting, Part I: Forecasting Modeling," Trans. IEEE, Vol. PAS-89, No. 7, pp. 1678-1688, September/October 1970.

59. J. Toyoda, M. Chen and Y. Inoue, "An Application of State Estimation to Short-Term Load Forecasting, Part II: Implementation," Trans. IEEE, Vol. PAS-89, No. 7, pp. 1683-1688, September/October 1970.

60. J. Toyoda and M. Chen, "A State Estimation-Type Approach to Practical Load Forecasting," Proc. PICA Conf. 1971, pp. 356-364.

61. P. C. Gupta and K. Yamada, "Adaptive Short-Term Forecasting of Hourly Loads Using Weather Information," Trans. IEEE, Vol. PAS-91, No. 5, pp. 2085-2094, September/October 1972.

62. A. A. Girgis, M. J. Settlage and E. B. Makram, "A Recursive Optimal Estimator for Power System Load Modeling and Forecasting," IEEE Regional Control Conference, 1986.

63. C. R. Szelag, "A Short-Term Forecasting Algorithm for Trunk Demand Servicing," The Bell System Technical Jour., Vol. 61, No. 1, January 1982, pp. 67-97.

64. K. L. S. Sharma and A. K. Mahalanabis, "Recursive Short-Term Load Forecasting Algorithm," Proc. IEEE, Vol. 121, No. 1, pp. 59-62, 1974.

65. G. Singh, K. K. Biswas, and A. K. Mahalanabis, "Power System Load Forecasting, Using Smoothing Techniques," Int. J. Syst. Sci., Vol. 9, No. 4, pp. 363-368, 1978.

66. F. D. Galiana and F. C. Schweppe, "A Weather-Dependent Probabilistic Model for Short-Term Load Forecasting," IEEE Winter Power Meeting, 1972, paper no. C72 171-2.

67. F. D. Galiana, E. Hanschin, and A. R. Fiechter, "Identification of Stochastic Electric Load Model from Physical Data," IEEE Trans. Automat. Contr., Vol. AC-19, No. 6, pp. 887-893, 1974.

68. V. Panuska and J. P. Koutchouk, "Electrical Power System Load Modelling by Two-Stage Stochastic Approximation Procedure," Proc. 6th Triennial World IFAC Congress, Part IIA, 1975.

69. V. Panuska, "Short-Term Forecasting of Electric Power System Load from a Weather-Dependent Model," IFAC Symp. Automat. Contr. Proteciton of Electric Power Syst., Melbourne, Feb. 1977, pp. 414-418.

70. R. Campo and P. Ruiz, "Adaptive Weather-Sensitive Short-Term Load Forecast," IEEE/PES 1986 Summer Meeting, Mexico City, Mexico, July 1986, paper no. 86 SM 305-7.

71. A. S. Dehdashti, J. R. Judor and M. C. Smith, "Forecasting Recognition," IEEE Trans. on Power Apparatus and Systems, Vol. PAS-101, No. 9, September 1982, pp. 3290-3294.

72. K. Srinivasan and R. Pronovost, "Short Term Load Forecasting Using Multiple Correlation Models," Trans. IEEE, Vol. PAS-94, No. 5, 1854-1857, September/October 1975.

73. D. W. Bunn, "Experimental Study of a Bayesian Method for Daily Electricity Load Forecasting," Appl. Math. Modelling, 1980, Vol. 4, April, pp. 113-116.

74. G. Singh, M. R. Mukerjee, and N. Sharma, "Multinode Load Forecasting Using Time Series," Proc. IFAC Symp. on Computer Applications in Large Scale Power Systems, India, Vol. 1, 1979, pp. 288-294.

75. R. L. Kashyap, "Estimation of Parameters in a Partially Specified System," Proc. 9th Allerton Conf. Circuits and Syst. USA.

76. M. R. McRae, R. M. Scheer, and B. A. Smith, "Integrating Load Management Programs into Utility Operations and Planning with a Load Reduction Forecasting System," IEEE/PES 1984 Summer Meeting, Seattle, Washington, July 1984, paper no. 84 SM 578-1.

77. D. W. Ross, G. B. Ackerman and R. Bischke, "Short-Term Prediction for Economic Dispatch of Generation," Proc. PICA Conf., 1979, pp. 198-204.

78. H. L. Willis and J. E. D. Northcote-Green, "A Hierarchical Recursive Method for Substantially Improving Trending of Small Area Load Forecasts," IEEE Trans. on PAS, Vol. PAS-101, No. 6, June 1982, pp. 1776-1783.

79. J. H. Broehl, "An End-Use Approach to Demand Forecasting," IEEE Trans. on PAS, Vol. PAS-100, No. 6, June 1981, pp. 2714-2718.

80. C. A. Letter and R. L. Sullivan, "A User Oriented Approach to Electric Demand Forecasting Using Interactive Graphics," Proc. PICA Conf., 1977, pp. 237-246.

81. B. Krogh, E. S. deLlinas and D. Lesser, "Design and Implementation of an On-Line Load Forecasting Algorithm," IEEE Trans. on PAS, Vol. PAS-101, No. 9, September 1982, pp. 3284-3289.

82. W. G. Michaelson and R. B. Comerford, "Forecasting and Computers: The Multi-Model Approach," Proc. PICA Conf., 1977, pp. 247-251.

83. S. Rahman and M. Baba, "Software Design and Evaluation of a Microcomputer based Automatic Load Forecasting System," IEEE Transaction on Power Systems, Vol. 4, No. 2, pp. 782-787, 1989.

84. S. Rahman and M Baba, "An Integrated Load Forecasting-Load Management Simulator: Its Design and Performance," IEEE Transaction on Power Systems, Vol. 4, No. 1, pp. 184-189, 1989.

85. S. Rahman, "An Expert System Approach to Adaptive Load Forecasting", Working Paper, Electrical Engineering Dept., Virginia Tech, June 1987.

86. R. Forsyth, "Expert Systems - Principles and Case Studies", Chapman and Hall Ltd., 1984.

87. Z. Z. Zhang, G. G. Hope, and O. P. Malik, "Expert Systems in Electric Power Systems: A Bibliographical Survey," IEEE/PES Winter Meeting 1989, New York N.Y., paper no. 89 WM 212-2.

88. D. Nau, "Expert Computer System, "COMPUTER, vol.16, No.2., Feb. 1983, pp.63-85.

89. W. Myers,"Introduction to Expert Systems,"IEEE EXPERT, Spring 1986, pp. 101-109.

90. D. Waterman," A Guide to Expert Systems," Addison-Wasley Publishing Co., 1986.

91. A. A. Girgis, and M. B. Johns, "A Hybrid expert System for Faulted Section Identification, Fault type Classification and Selection of faulted Location Algorithm," IEEE/PES 1988 Summer Meeting, paper no. 88 SM 525-8.

92. D. Kanga, "Application of Intelligent Computer_Aided Design Techniques to Power Plants Design and Operation," IEEE Trans. on Energy Conversion, no.1, Dec. 1987, pp. 592-597.

93. Y. Koho, et. al., "An Intelligent Support System for Power System Planning," IEEE Trans. on Power Systems, v.PWRS-1, no.X, May 1986, pp. 67-75.

94. H. Amelink, A. M. Forte, and R. P. Guberman, "Dispatcher Alarm and Message Processing," IEEE Trans. on Power Systems, v.PWRS-1, no.3, Aug. 1986, pp. 188-194.

95. K. Tomsovic, C. Liu, P. Ackerman, and S. Pope, " An Expert System as a Dispatchers' Aid for the Isolation of Line Section Faults," IEEE Trans. on Power Delivery, v.PWRD-2, no.3, July 1987, pp. 736-743.

96. T. Sakajuchi, and K. Matsumoto, "Development of Knowledge-Based Systems for Power System Restoration," IEEE Trans. on PAS. vol.102, no.2, Feb. 1983, pp. 320-329.

97. R.D. Masiello et. al., "Review of EPRI Project on Power Training Simulator Implementation," 1984 EEI Engineering Computer Form, Atlanta Ga.

98. C. Liu, and K. Tomsovic, "An Expert System Assisting Decision-Making of Reactive Power/Voltage Control," IEEE Trans. on Power Systems, v.PRWS-1, no.3, Aug. 1986 pp. 195-201.

99. M. Baba and S. Rahman ,"Expert Systems and Their Applications in Energy Management, "Proc. IEEE Southeast Conference, Richmond, Virginia, 1986.

100. S. N. Talukdar and E. Cardozo, "Artificial Intelligence Technologies for Power System Operations," EPRI EL-4342, Project 1999-7, Final Report, January 1986.

101. S. Talukdar,E. Cardozo, L. Leao, "TOAST: The Power System Operators' Assistant," COMPUTER, vol. 19, No.7,July 1986, pp. 53-60.

102. S.J. Cheng, O.P. Mailk and G.S. Hope, "An expert System for Voltage and Reactive Power Control of a Power System," IEEE/PES Winter Meeting (1988), paper no. 88WM153-9.

103. G. M. Jenkins, "Practical Experience with Modeling and Forecasting Time Series,"G. Jenkins & Partners (Overseas) Ltd., 1979.

104. E. A. Robinson and M. T. Silvia, "Digital Foundation of the Time Series Analysis: The Box-Jenkins Approach," Holden-Day, Inc., 1979.

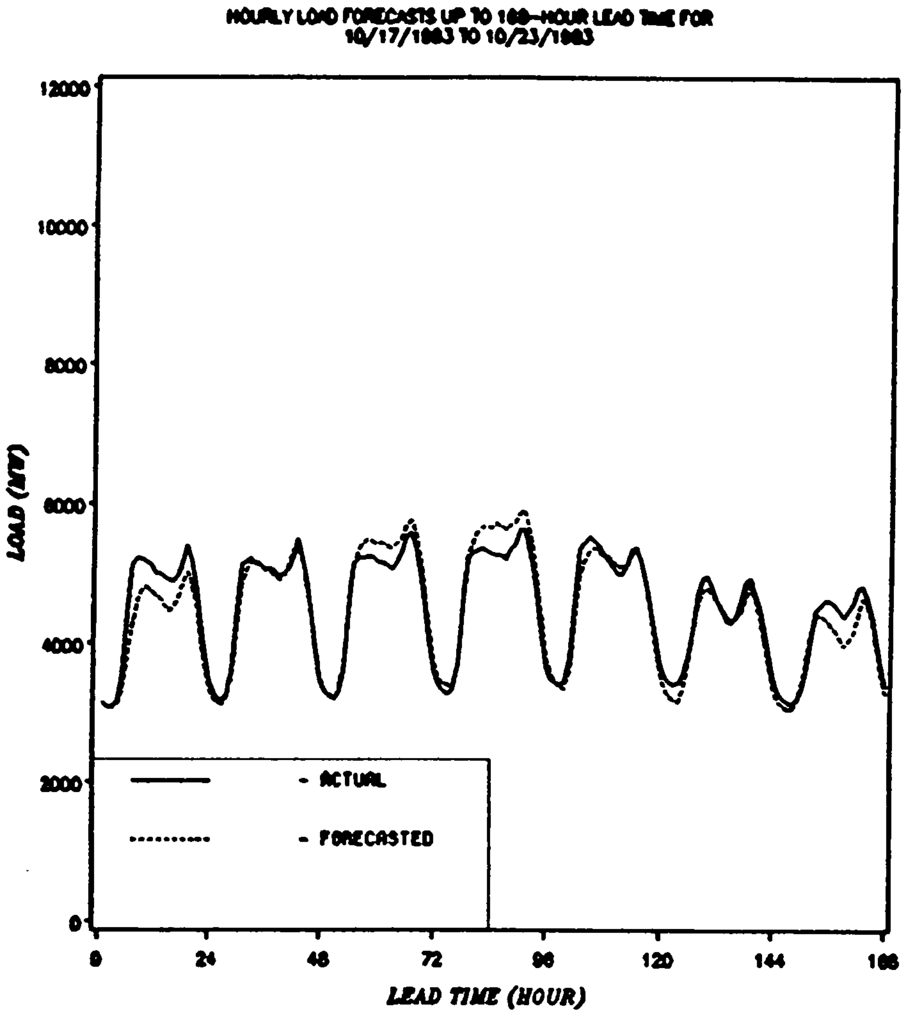
105. John P. Murphy, "Wind Chill Index," Weather Services Corporation, Bedford, Massachusetts, Personal Communication, July 1985.

106. S. Rahman, "An Expert System Based Load Forecasting Technique: Its Development and Application," Working Paper, Electrical Engineering Dept., Virginia Tech, October 1988.

Appendix A

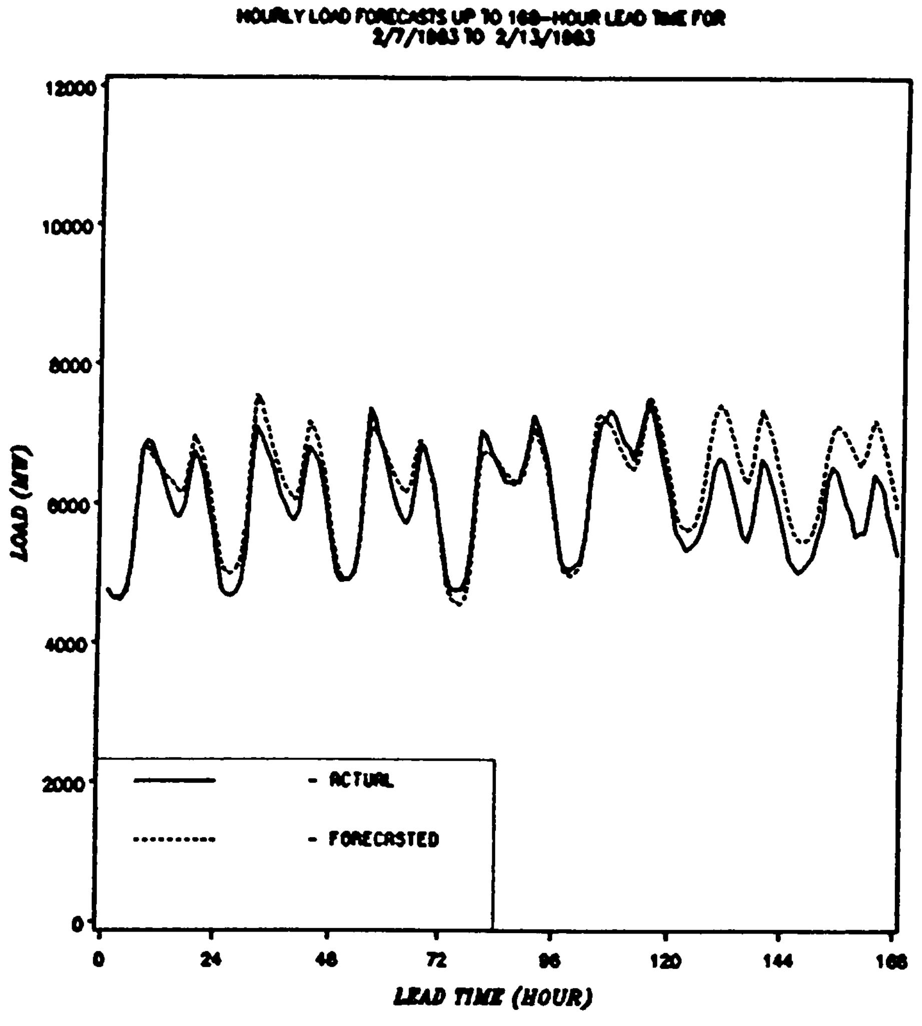
TIME SERIES WEEKLY LOAD PREDICTIONS

The results of the prediction using the time series approach discussed in chapter 5 has been displayed for the summer season. The results of prediction for the other three seasons are shown in Figure 29 through Figure 34.



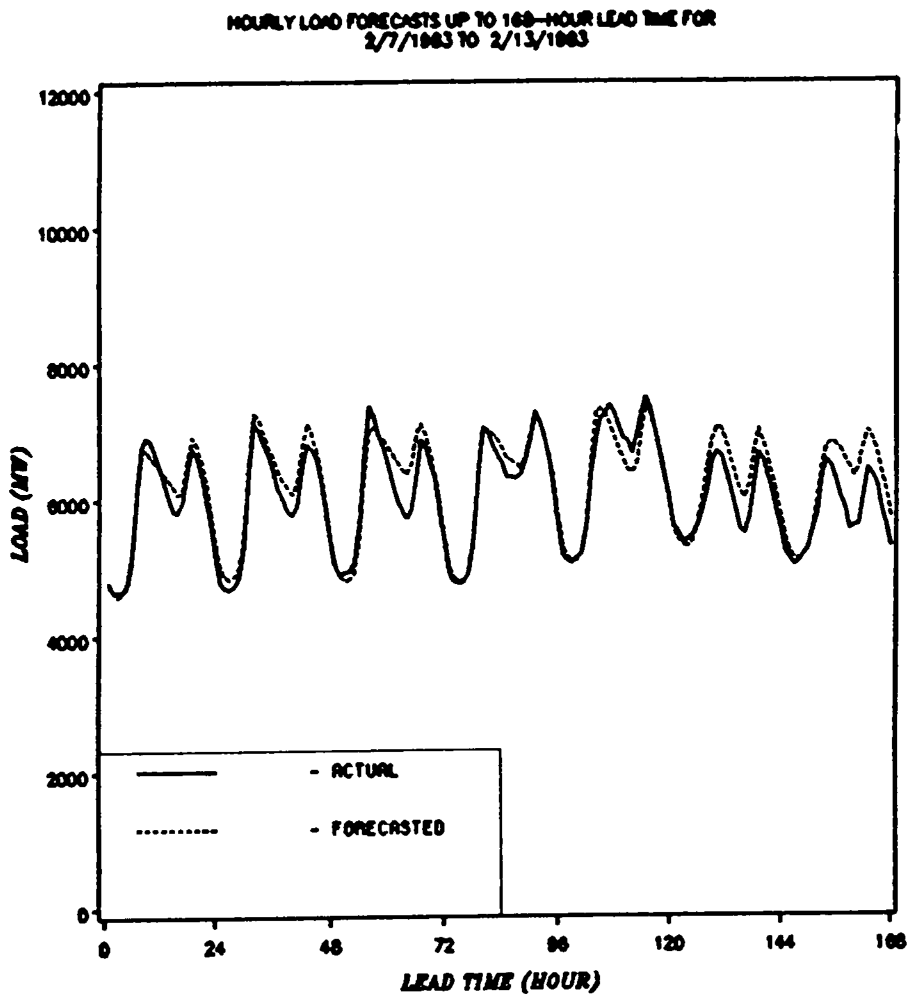
MONTH:OCTBER 83
DATA BASE 9/19 TO 10/16/83
MODEL: D(1,24)(1,2,12)(23,24,25,48,72,96,120,144)Y=(168)A

Figure 29. Actual and Forecasted (seasonal ARIMA) Hourly Load Data for Fall Model (17-23 October 1983)



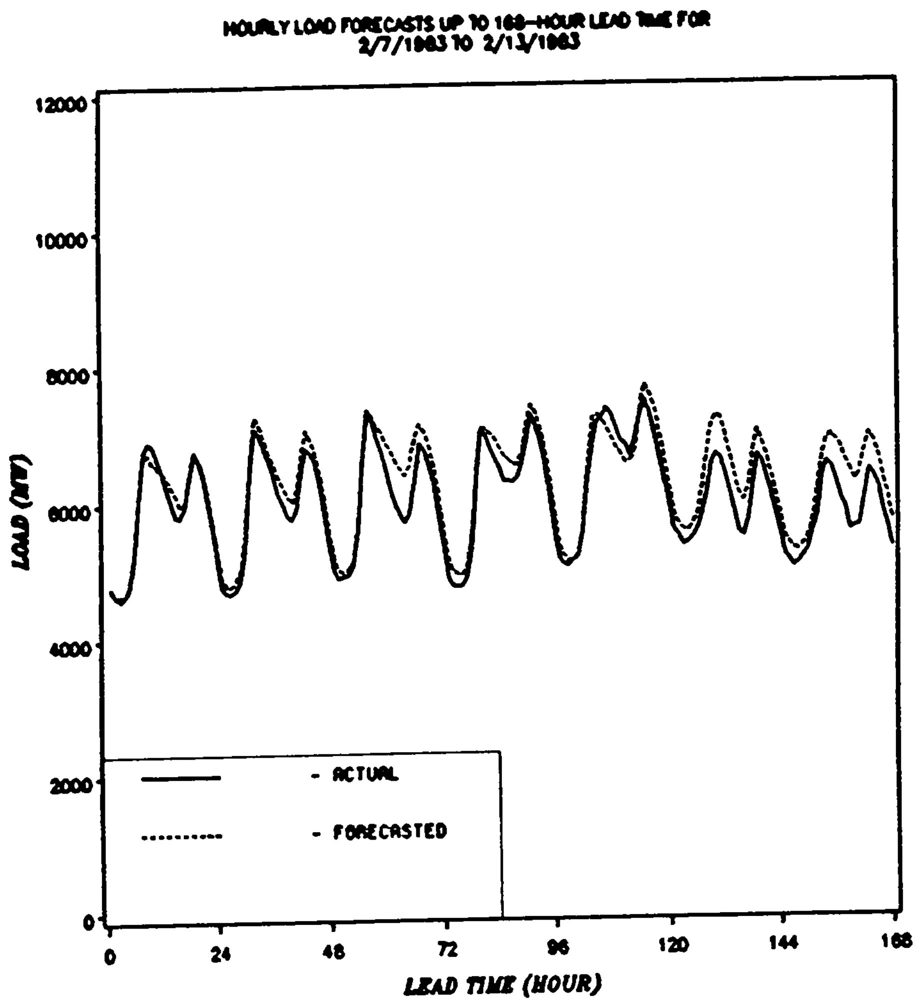
MONTH:FEBRUARY 83
DATA BASE 1/10 TO 2/6/83
MODEL: D(1,24)(1)(23,24,25,48,72,96,120,144)Y=(168)A

Figure 30. Actual and Forecasted (seasonal ARIMA) Hourly Load Data for Winter Model (7-13 February 1983)



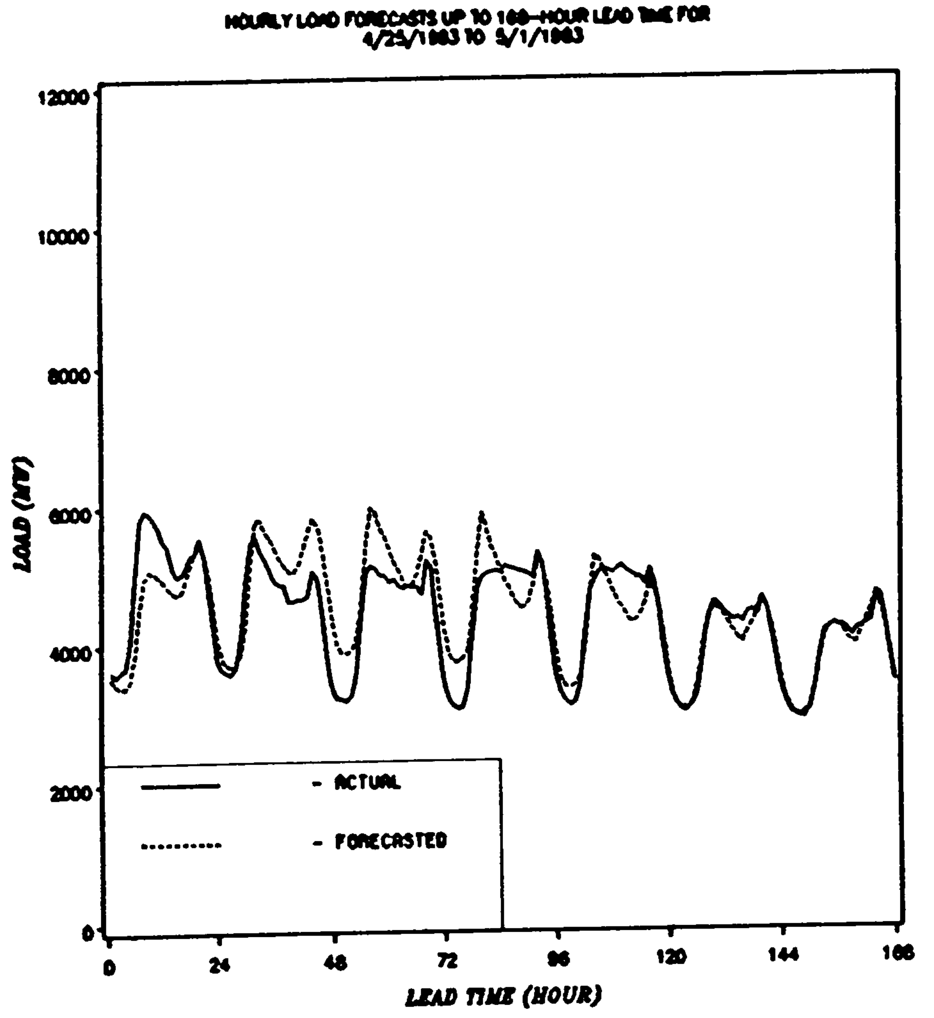
MONTH:FEBRUARY 83
DATA BASE 1/10 TO 2/6/83
MODEL: D(1,24)Y=D(1,24)(2)X+(1/((1,3,6,9)(23,24,48,72,96,120,144)(168)))A2
WHERE D(1,24)(2)(24,25,48,72,96,120,144)X=A1 AND X=DBT

Figure 31. Actual and Forecasted (TF Model) Hourly Load Data for Winter Model (7-13 February 1983) Using Forecasted Input values



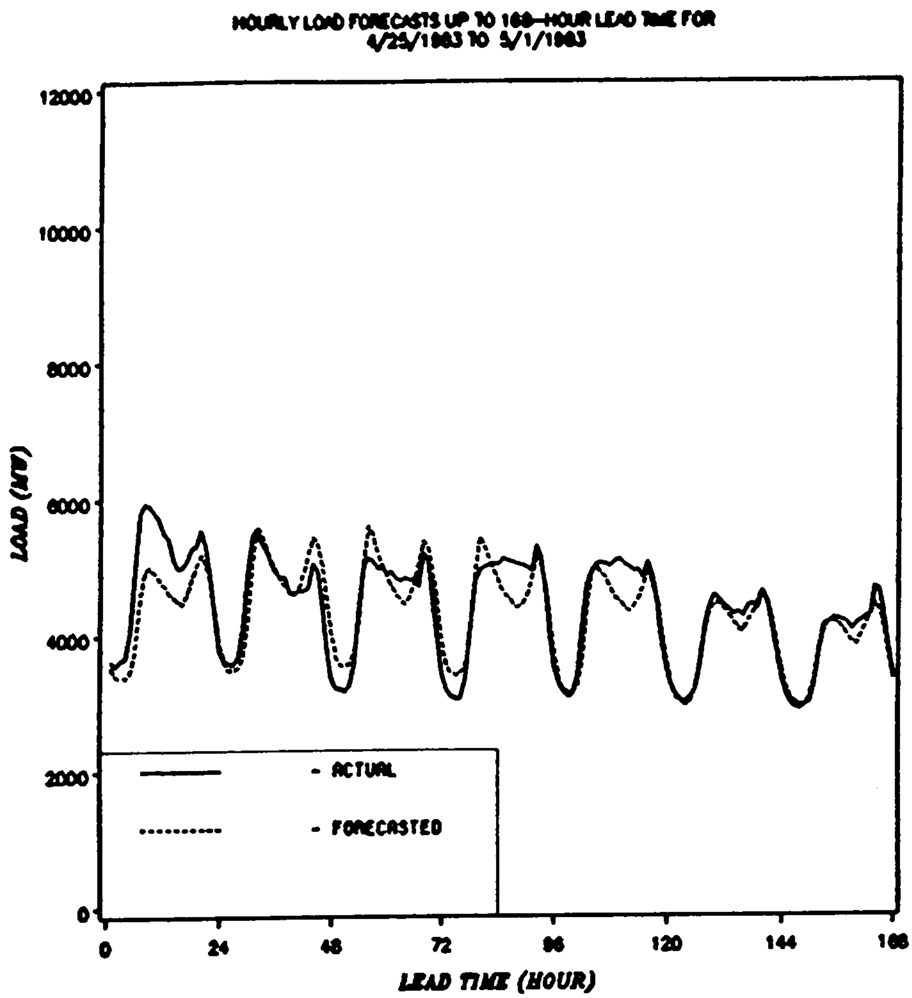
MONTH:FEBRUARY 83
DATA BASE 1/10 TO 2/6/83
MODEL: D(1,24)Y=D(1,24)(2)X+(1/((1,3,6,9)(23,24,48,72,96,120,144)(168)))A2
WHERE D(1,24)(2)(24,25,48,72,96,120,144)X=A1 AND X=DBT (ACTUAL)

Figure 32. Actual and Forecasted (TF Model) Hourly Load Data for Winter Model (7-13 February 1983) Using Actual Input Values



MONTH:APRIL 83
DATA BASE 3/28 TO 4/24/83
MODEL: D(1,24)(1)(23,24,25,48,72,96,120,144)(168)Y=A

Figure 33. Actual and Forecasted (seasonal ARIMA) Hourly Load Data for Spring Model (25 April to 1 May 1983)



MONTH:APRIL 83
DATA BASE 3/28 TO 4/24/83
MODEL: D(1,24)(1,3)(23,24,25,48,72,96,120,144)(168)Y=A
WHERE D(1,24)(1,11)(24,48,72,96,120)X=A

Figure 34. Actual and Forecasted (TF ARIMA) Hourly Load Data for Spring Model (25 April to 1 May 1983) Using Forecasted Input values

Appendix B

WEEKLY LOAD FORECAST ERROR DISTRIBUTIONS

This Appendix contains the one week lead time absolute percent load forecast error distributions using the knowledge-base approach presented in chapter 6. These distributions are shown in Table 36 through Table 43. for the four best lag time temperature effect (.i.e, 12, 16, 20, and 24 hours). Tables 36 to 39 show these error distributions as calculated with respect to the hourly load while Tables 40 to 43 show these results as calculated with respect to the daily peak.

Table 36. One-Week Lead Time Absolute Percent Forecast Error (wrt Hourly Load) Distribution with 12-hour Lag Time Temperature Effect

DAY	0<= ? <1	1<= ? <2	2<= ? <3	3<= ? <4	4<= ? <5	5<= ? <6	6<= ? <7	7<= ? <8	8<= ? <10	10<= ? <12	12<= ? <15	15<= ? <20	>=20 ?
1	6	5	6	5	1	1	0	0	0	0	0	0	0
2	4	4	3	7	5	1	0	0	0	0	0	0	0
3	13	7	2	2	0	0	0	0	0	0	0	0	0
4	2	8	10	3	1	0	0	0	0	0	0	0	0
5	10	6	5	1	1	1	0	0	0	0	0	0	0
6	6	6	8	3	1	0	0	0	0	0	0	0	0
7	4	7	5	1	2	3	1	1	0	0	0	0	0
8	2	5	7	6	2	2	0	0	0	0	0	0	0
9	7	5	4	6	2	0	0	0	0	0	0	0	0
10	3	5	3	5	5	0	3	0	0	0	0	0	0
11	10	8	4	1	0	1	0	0	0	0	0	0	0
12	3	5	6	6	4	0	0	0	0	0	0	0	0
13	2	4	4	7	2	0	4	0	1	0	0	0	0
14	6	0	5	3	3	1	1	1	2	1	1	0	0
15	3	2	1	1	2	1	1	4	4	3	0	2	0
16	5	2	1	2	6	4	0	0	4	0	0	0	0
17	3	4	2	4	6	4	1	0	0	0	0	0	0
18	0	1	1	10	4	4	2	1	1	0	0	0	0
19	2	2	3	4	9	3	0	1	0	0	0	0	0
20	6	5	5	5	3	0	0	0	0	0	0	0	0
21	0	1	1	0	4	3	5	6	4	0	0	0	0
22	5	6	8	2	3	0	0	0	0	0	0	0	0
23	5	5	6	6	2	0	0	0	0	0	0	0	0
24	4	16	3	1	0	0	0	0	0	0	0	0	0
25	6	6	5	2	2	3	0	0	0	0	0	0	0
26	11	4	3	4	0	0	0	1	1	0	0	0	0
27	9	4	6	4	1	0	0	0	0	0	0	0	0
28	5	2	1	9	3	2	2	0	0	0	0	0	0
29	1	4	3	8	6	0	1	1	0	0	0	0	0
30	5	5	2	1	2	5	3	1	0	0	0	0	0
31	11	8	2	2	0	0	1	0	0	0	0	0	0
TOTAL	159	152	125	121	82	39	25	17	17	4	1	2	0
%	21.4	20.4	16.8	16.3	11.0	5.2	3.4	2.3	2.3	0.5	0.1	0.3	0
CUMM.	21.4	41.8	58.6	74.9	85.9	91.1	94.5	96.8	99.1	99.6	99.7	100.	100.

Table 37. One-Week Lead Time Absolute Percent Forecast Error (wrt Hourly Load) Distribution with 16-hour Lag Time Temperature Effect

DAY	0<= ? <1	1<= ? <2	2<= ? <3	3<= ? <4	4<= ? <5	5<= ? <6	6<= ? <7	7<= ? <8	8<= ? <10	10<= ? <12	12<= ? <15	15<= ? <20	>=20 ?
1	9	3	5	6	0	1	0	0	0	0	0	0	0
2	3	5	4	9	2	1	0	0	0	0	0	0	0
3	9	7	5	3	0	0	0	0	0	0	0	0	0
4	4	8	7	4	1	0	0	0	0	0	0	0	0
5	6	10	2	4	2	0	0	0	0	0	0	0	0
6	3	9	7	3	2	0	0	0	0	0	0	0	0
7	4	9	4	1	1	3	2	0	0	0	0	0	0
8	1	4	8	5	2	4	0	0	0	0	0	0	0
9	6	6	4	6	1	1	0	0	0	0	0	0	0
10	6	1	7	6	1	2	1	0	0	0	0	0	0
11	11	8	2	2	0	1	0	0	0	0	0	0	0
12	7	4	4	6	2	1	0	0	0	0	0	0	0
13	2	8	5	6	1	0	2	0	0	0	0	0	0
14	5	1	6	2	1	3	1	1	1	2	1	0	0
15	3	5	0	1	1	5	1	2	1	3	0	2	0
16	3	4	2	6	3	2	2	2	0	0	0	0	0
17	3	4	4	5	7	1	0	0	0	0	0	0	0
18	0	0	3	7	8	2	1	2	1	0	0	0	0
19	1	5	5	7	5	0	0	1	0	0	0	0	0
20	2	5	9	5	2	1	0	0	0	0	0	0	0
21	1	0	1	2	6	3	5	4	2	0	0	0	0
22	3	6	8	1	3	3	0	0	0	0	0	0	0
23	11	4	5	2	2	0	0	0	0	0	0	0	0
24	6	8	7	3	0	0	0	0	0	0	0	0	0
25	4	7	6	1	4	2	0	0	0	0	0	0	0
26	10	7	1	3	1	0	0	1	1	0	0	0	0
27	8	6	8	2	0	0	0	0	0	0	0	0	0
28	4	3	2	6	5	2	2	0	0	0	0	0	0
29	3	3	4	3	9	1	0	1	0	0	0	0	0
30	6	2	4	1	2	5	2	2	0	0	0	0	0
31	11	5	5	2	0	0	1	0	0	0	0	0	0
TOTAL	155	157	144	120	74	44	20	16	6	5	1	2	0
%	20.8	22.6	20.3	14.0	10.8	5.1	2.8	1.5	1.2	0.5	0.1	0.3	0
CUMM.	20.8	43.4	63.7	77.7	88.5	93.6	96.4	97.9	99.1	99.6	99.7	100.	100.

Table 38. One-Week Lead Time Absolute Percent Forecast Error (wrt Hourly Load) Distribution with 20-hour Lag Time Temperature Effect

DAY	0<= ? <1	1<= ? <2	2<= ? <3	3<= ? <4	4<= ? <5	5<= ? <6	6<= ? <7	7<= ? <8	8<= ? <10	10<= ? <12	12<= ? <15	15<= ? <20	>=20 ?
1	10	5	3	2	4	0	0	0	0	0	0	0	0
2	5	5	6	5	2	1	0	0	0	0	0	0	0
3	10	6	6	2	0	0	0	0	0	0	0	0	0
4	5	9	4	5	1	0	0	0	0	0	0	0	0
5	2	11	5	4	2	0	0	0	0	0	0	0	0
6	5	6	7	4	1	1	0	0	0	0	0	0	0
7	5	10	2	1	3	1	2	0	0	0	0	0	0
8	1	4	3	9	3	2	2	0	0	0	0	0	0
9	6	6	5	4	2	1	0	0	0	0	0	0	0
10	5	5	5	6	2	1	0	0	0	0	0	0	0
11	9	9	5	0	0	1	0	0	0	0	0	0	0
12	7	5	4	2	4	2	0	0	0	0	0	0	0
13	8	5	6	3	1	0	1	0	0	0	0	0	0
14	6	2	5	2	1	0	4	0	2	1	1	0	0
15	2	6	1	2	5	0	2	0	1	3	0	2	0
16	2	4	6	2	2	6	0	1	1	0	0	0	0
17	2	9	4	5	4	0	0	0	0	0	0	0	0
18	0	0	6	5	7	2	1	2	1	0	0	0	0
19	1	6	9	2	5	0	1	0	0	0	0	0	0
20	1	3	8	7	5	0	0	0	0	0	0	0	0
21	1	0	2	5	6	3	2	3	2	0	0	0	0
22	2	3	11	2	2	2	2	0	0	0	0	0	0
23	11	6	3	1	1	2	0	0	0	0	0	0	0
24	5	9	3	5	2	0	0	0	0	0	0	0	0
25	4	7	5	2	4	2	0	0	0	0	0	0	0
26	8	6	6	1	1	0	0	1	1	0	0	0	0
27	7	8	7	2	0	0	0	0	0	0	0	0	0
28	4	3	3	6	3	2	2	1	0	0	0	0	0
29	4	2	3	6	4	4	0	0	1	0	0	0	0
30	6	2	4	1	2	4	2	3	0	0	0	0	0
31	11	6	4	1	1	1	0	0	0	0	0	0	0
TOTAL	155	168	151	104	80	38	21	11	9	4	1	2	0
%	21.9	21.4	20.4	14.4	9.7	4.4	4.0	1.4	1.6	0.4	0.3	0.1	0
CUMM.	21.9	43.3	63.7	78.2	87.9	92.3	96.3	97.6	99.2	99.6	99.9	100.	100.

Table 39. One-Week Lead Time Absolute Percent Forecast Error (wrt Hourly Load) Distribution with 24-hour Lag Time Temperature Effect

DAY	0<= ? <1	1<= ? <2	2<= ? <3	3<= ? <4	4<= ? <5	5<= ? <6	6<= ? <7	7<= ? <8	8<= ? <10	10<= ? <12	12<= ? <15	15<= ? <20	>=20 ?
1	11	4	1	2	4	2	0	0	0	0	0	0	0
2	7	7	1	7	1	1	0	0	0	0	0	0	0
3	11	5	7	1	0	0	0	0	0	0	0	0	0
4	7	9	4	3	1	0	0	0	0	0	0	0	0
5	1	9	9	3	2	0	0	0	0	0	0	0	0
6	4	4	8	6	1	1	0	0	0	0	0	0	0
7	5	11	1	2	2	2	1	0	0	0	0	0	0
8	1	4	3	6	6	0	4	0	0	0	0	0	0
9	6	3	6	6	2	0	1	0	0	0	0	0	0
10	5	8	7	1	2	1	0	0	0	0	0	0	0
11	8	9	5	1	1	0	0	0	0	0	0	0	0
12	5	5	4	3	4	3	0	0	0	0	0	0	0
13	8	6	4	5	0	0	1	0	0	0	0	0	0
14	6	3	7	0	0	1	3	0	2	1	1	0	0
15	1	6	1	3	5	0	2	1	1	2	1	1	0
16	2	3	5	3	3	5	1	1	1	0	0	0	0
17	5	7	3	5	4	0	0	0	0	0	0	0	0
18	0	3	6	3	7	1	1	2	1	0	0	0	0
19	1	5	7	7	3	0	1	0	0	0	0	0	0
20	1	3	8	7	3	2	0	0	0	0	0	0	0
21	1	0	2	9	4	3	2	0	3	0	0	0	0
22	3	4	10	0	2	2	1	2	0	0	0	0	0
23	10	6	1	3	1	1	2	0	0	0	0	0	0
24	5	5	8	2	3	1	0	0	0	0	0	0	0
25	7	2	7	4	1	2	1	0	0	0	0	0	0
26	7	7	7	0	1	0	1	0	1	0	0	0	0
27	11	6	4	2	1	0	0	0	0	0	0	0	0
28	4	3	5	6	2	1	2	1	0	0	0	0	0
29	4	3	3	5	3	3	2	0	1	0	0	0	0
30	5	3	4	1	2	0	4	3	2	0	0	0	0
31	11	6	4	1	1	1	0	0	0	0	0	0	0
TOTAL	163	159	152	107	72	33	30	10	12	3	2	1	0
%	21.9	21.4	20.4	14.4	9.7	4.4	4.0	1.3	1.6	0.4	0.3	0.1	0
CUMM.	21.9	43.3	63.7	78.2	87.9	92.3	96.3	97.6	99.2	99.6	99.9	100.	100.

Table 40. One-Week Lead Time Absolute Percent Forecast Error (wrt Daily Peak) Distribution with 12-hour Lag Time Temperature Effect

DAY	0<= ? <1	1<= ? <2	2<= ? <3	3<= ? <4	4<= ? <5	5<= ? <6	6<= ? <7	7<= ? <8	8<= ? <10	10<= ? <12	12<= ? <15	15<= ? <20	>=20 ?
1	6	7	8	2	0	1	0	0	0	0	0	0	0
2	5	7	6	4	1	1	0	0	0	0	0	0	0
3	13	9	2	0	0	0	0	0	0	0	0	0	0
4	4	11	7	2	0	0	0	0	0	0	0	0	0
5	13	8	0	1	2	0	0	0	0	0	0	0	0
6	10	7	4	2	1	0	0	0	0	0	0	0	0
7	7	6	3	2	1	3	2	0	0	0	0	0	0
8	3	8	5	4	2	2	0	0	0	0	0	0	0
9	10	3	7	3	1	0	0	0	0	0	0	0	0
10	6	3	3	6	3	1	2	0	0	0	0	0	0
11	13	7	2	1	0	1	0	0	0	0	0	0	0
12	5	8	5	6	0	0	0	0	0	0	0	0	0
13	3	5	3	8	0	0	4	0	1	0	0	0	0
14	6	2	5	2	4	1	2	1	1	0	0	0	0
15	3	3	1	2	2	2	1	4	3	1	2	0	0
16	7	1	3	2	3	5	1	2	0	0	0	0	0
17	5	3	4	5	4	2	1	0	0	0	0	0	0
18	0	3	8	4	5	1	2	0	1	0	0	0	0
19	3	3	6	9	1	2	0	0	0	0	0	0	0
20	8	6	8	2	0	0	0	0	0	0	0	0	0
21	1	1	1	3	4	6	1	3	4	0	0	0	0
22	8	9	3	3	1	0	0	0	0	0	0	0	0
23	5	8	6	4	1	0	0	0	0	0	0	0	0
24	11	10	2	1	0	0	0	0	0	0	0	0	0
25	6	8	4	3	1	2	0	0	0	0	0	0	0
26	15	1	6	0	1	0	1	0	0	0	0	0	0
27	11	9	3	1	0	0	0	0	0	0	0	0	0
28	5	3	8	3	5	0	0	0	0	0	0	0	0
29	2	5	9	6	2	0	0	0	0	0	0	0	0
30	7	3	4	5	1	2	2	0	0	0	0	0	0
31	14	6	2	1	0	1	0	0	0	0	0	0	0
TOTAL	215	173	138	97	46	33	19	10	10	1	2	0	0
%	28.9	22.3	18.5	13.0	6.2	4.4	2.6	1.3	1.3	0.1	0.3	0	0
CUMM.	28.9	52.2	70.7	83.7	89.9	94.4	97.0	98.3	99.6	99.7	100.0	100.	100.

Table 41. One-Week Lead Time Absolute Percent Forecast Error (wrt Daily Peak) Distribution with 16-hour Lag Time Temperature Effect

DAY	0<= ? <1	1<= ? <2	2<= ? <3	3<= ? <4	4<= ? <5	5<= ? <6	6<= ? <7	7<= ? <8	8<= ? <10	10<= ? <12	12<= ? <15	15<= ? <20	>=20 ?
1	9	6	6	2	1	0	0	0	0	0	0	0	0
2	4	10	4	4	2	0	0	0	0	0	0	0	0
3	14	6	3	1	0	0	0	0	0	0	0	0	0
4	6	8	8	1	1	0	0	0	0	0	0	0	0
5	9	9	3	3	0	0	0	0	0	0	0	0	0
6	8	8	6	1	1	0	0	0	0	0	0	0	0
7	8	6	3	1	1	3	2	0	0	0	0	0	0
8	4	6	5	4	3	2	0	0	0	0	0	0	0
9	10	3	7	3	1	0	0	0	0	0	0	0	0
10	6	4	5	5	1	3	0	0	0	0	0	0	0
11	14	6	2	1	0	1	0	0	0	0	0	0	0
12	8	3	7	3	3	0	0	0	0	0	0	0	0
13	2	9	6	4	1	0	2	0	0	0	0	0	0
14	5	3	5	2	5	0	1	1	1	1	0	0	0
15	4	4	1	1	3	4	3	0	2	0	2	0	0
16	4	5	3	3	3	4	2	0	0	0	0	0	0
17	7	2	8	4	2	1	0	0	0	0	0	0	0
18	0	3	8	4	5	1	1	1	1	0	0	0	0
19	4	6	7	4	2	1	0	0	0	0	0	0	0
20	3	10	9	1	1	0	0	0	0	0	0	0	0
21	1	1	4	3	5	3	3	2	2	0	0	0	0
22	5	11	3	1	3	1	0	0	0	0	0	0	0
23	11	5	6	2	0	0	0	0	0	0	0	0	0
24	8	10	6	0	0	0	0	0	0	0	0	0	0
25	7	7	4	3	2	1	0	0	0	0	0	0	0
26	13	5	4	0	1	0	1	0	0	0	0	0	0
27	9	10	5	0	0	0	0	0	0	0	0	0	0
28	5	2	9	3	4	1	0	0	0	0	0	0	0
29	3	3	10	4	4	0	0	0	0	0	0	0	0
30	6	4	5	3	2	2	2	0	0	0	0	0	0
31	14	6	2	1	0	1	0	0	0	0	0	0	0
TOTAL	211	181	164	72	57	29	17	4	6	1	2	0	0
%	28.4	24.3	22.0	9.7	7.7	3.8	2.3	0.5	0.8	0.1	0.3	0	0
CUMM.	28.4	52.7	74.7	84.4	92.1	96.0	98.3	98.8	99.6	99.7	100.	100.	100.

Table 42. One-Week Lead Time Absolute Percent Forecast Error (wrt Daily Peak) Distribution with 20-hour Lag Time Temperature Effect

DAY	0<= ? <1	1<= ? <2	2<= ? <3	3<= ? <4	4<= ? <5	5<= ? <6	6<= ? <7	7<= ? <8	8<= ? <10	10<= ? <12	12<= ? <15	15<= ? <20	>=20 ?
1	12	4	6	1	1	0	0	0	0	0	0	0	0
2	7	8	2	5	2	0	0	0	0	0	0	0	0
3	12	8	3	1	0	0	0	0	0	0	0	0	0
4	9	6	6	2	1	0	0	0	0	0	0	0	0
5	6	10	5	3	0	0	0	0	0	0	0	0	0
6	7	8	4	4	0	1	0	0	0	0	0	0	0
7	9	6	2	2	2	1	2	0	0	0	0	0	0
8	4	4	6	3	3	2	2	0	0	0	0	0	0
9	9	4	7	3	1	0	0	0	0	0	0	0	0
10	7	6	3	5	2	1	0	0	0	0	0	0	0
11	11	9	3	0	0	1	0	0	0	0	0	0	0
12	7	6	5	3	3	0	0	0	0	0	0	0	0
13	9	8	3	2	1	0	1	0	0	0	0	0	0
14	6	2	6	2	2	2	1	0	2	1	0	0	0
15	4	5	1	3	5	0	2	0	2	1	1	0	0
16	4	4	6	0	2	8	0	0	0	0	0	0	0
17	7	5	6	3	3	0	0	0	0	0	0	0	0
18	0	3	8	3	6	1	1	1	1	0	0	0	0
19	3	7	7	4	3	0	0	0	0	0	0	0	0
20	2	7	9	6	0	0	0	0	0	0	0	0	0
21	1	1	5	6	2	5	2	2	0	0	0	0	0
22	5	7	7	0	3	1	1	0	0	0	0	0	0
23	12	7	2	2	1	0	0	0	0	0	0	0	0
24	6	9	6	3	0	0	0	0	0	0	0	0	0
25	7	6	5	4	1	1	0	0	0	0	0	0	0
26	10	7	5	0	1	0	1	0	0	0	0	0	0
27	12	7	4	1	0	0	0	0	0	0	0	0	0
28	5	2	8	5	3	1	0	0	0	0	0	0	0
29	4	4	6	8	1	1	0	0	0	0	0	0	0
30	6	4	2	5	3	2	2	0	0	0	0	0	0
31	13	7	2	1	0	1	0	0	0	0	0	0	0
TOTAL	216	181	150	90	52	29	15	3	5	2	1	0	0
%	29.0	24.3	20.2	12.1	7.0	3.9	2.0	0.4	0.7	0.3	0.1	0	0
CUMM.	29.0	53.3	73.5	85.6	92.6	96.5	98.5	98.9	99.6	99.9	100.	100.	100.

Table 43. One-Week Lead Time Absolute Percent Forecast Error (wrt Daily Peak) Distribution with 24-hour Lag Time Temperature Effect

DAY	0<= ? <1	1<= ? <2	2<= ? <3	3<= ? <4	4<= ? <5	5<= ? <6	6<= ? <7	7<= ? <8	8<= ? <10	10<= ? <12	12<= ? <15	15<= ? <20	>=20 ?
1	11	5	3	3	1	1	0	0	0	0	0	0	0
2	9	6	3	4	2	0	0	0	0	0	0	0	0
3	12	8	3	1	0	0	0	0	0	0	0	0	0
4	10	6	5	2	1	0	0	0	0	0	0	0	0
5	4	11	7	1	1	0	0	0	0	0	0	0	0
6	4	11	6	2	1	0	0	0	0	0	0	0	0
7	11	5	1	2	2	3	0	0	0	0	0	0	0
8	4	4	5	3	4	2	2	0	0	0	0	0	0
9	7	5	8	3	1	0	0	0	0	0	0	0	0
10	8	7	5	1	3	0	0	0	0	0	0	0	0
11	14	6	3	0	1	0	0	0	0	0	0	0	0
12	7	3	5	5	4	0	0	0	0	0	0	0	0
13	8	8	5	2	0	0	1	0	0	0	0	0	0
14	6	4	6	1	1	3	0	2	0	1	0	0	0
15	2	5	3	4	4	0	2	0	2	2	0	0	0
16	4	5	4	1	2	8	0	0	0	0	0	0	0
17	10	3	4	5	2	0	0	0	0	0	0	0	0
18	2	3	7	4	4	1	1	1	1	0	0	0	0
19	5	4	6	6	3	0	0	0	0	0	0	0	0
20	2	8	6	4	4	0	0	0	0	0	0	0	0
21	1	2	8	3	4	2	3	1	0	0	0	0	0
22	5	7	5	2	2	1	2	0	0	0	0	0	0
23	11	6	3	2	2	0	0	0	0	0	0	0	0
24	8	4	7	4	1	0	0	0	0	0	0	0	0
25	7	6	7	1	2	1	0	0	0	0	0	0	0
26	8	9	5	0	1	0	1	0	0	0	0	0	0
27	12	7	4	0	1	0	0	0	0	0	0	0	0
28	5	5	7	3	2	2	0	0	0	0	0	0	0
29	4	3	8	5	3	0	1	0	0	0	0	0	0
30	6	4	2	3	5	1	3	0	0	0	0	0	0
31	13	6	3	1	0	1	0	0	0	0	0	0	0
TOTAL	220	176	154	78	64	26	16	4	3	3	0	0	0
%	29.6	23.7	20.7	10.5	8.6	3.4	2.2	0.5	0.4	0.4	0	0	0
CUMM.	29.6	53.2	73.9	84.4	93.0	96.5	98.7	99.2	99.6	100.	100.	100.	100.

Appendix C

ASSUMPTIONS USED FOR DIFFERENT LOAD MODELING TECHNIQUES

Significant assumptions in implementing these various modeling techniques are summarized in the following. The forecasting techniques to which these assumptions are applied are noted in parenthesis.

- The serial correlation among the load data is negligible (MLR).
- The relationship in each interval between the load and its explanatory variables is linear (MLR).
- The base load in each interval is constant for all weekdays in the period considered (MLR).

- The effect of load inertia can be obtained through a fixed relationship (namely the difference of the average of the previous 24 hours from that lagged by 3 hours) (MLR).

- The effect of the explanatory variables will stay the same during the modeling interval (MLR).

- The considered process is linear (STS, GES, SS).

- The considered process is stationary or can be transformed into stationary process by differencing (STS, SS).

- The noise series (or model error) is of zero mean and constant unknown variance and its observations are uncorrelated with each other (MLR, STS, GES, SS).

- The weekly seasonality is negligible (GES, SS).

- Small order model (up to 3 terms) is sufficient for building the load model (SS).

- The effect of the load control on the load forecast is neglected (MLR, STS, GES, SS, KBES).

- Accurate weather forecasts are available (MLR, KBES).

- The self-learning aspect of the expert system was tested on one year's data (KBES).

Appendix D

SAMPLES OF LOAD MODELS

The models that were developed using statistical techniques are demonstrated here for the UV, TF, and LR analysis.

Univariate analysis (UV)

The univaraite time series approach was applied to model the daily peak load, y(t), and the daily energy , e(t), for both summer and winter seasons. Four weeks of data for the daily peak and the daily energy were used in the development of these models in each season. The daily peak univariate model for the winter season was modeled as:

$$(1 - 0.243B + 0.307B^2)(1 - 0.480B^7)\nabla_1 y(t) = a(t) \qquad (D1)$$

For the summer season, the daily peak univariate model was identified and its parameters estimated using the centered series, $\tilde{y}$ (t), as:

$$(1 - 0.806B)\tilde{y}(t) = a(t) \qquad (D2)$$

The daily energy univariate models for both winter and summer seasons were identified and their parameters estimated, using four weeks of data for the centered series, $\tilde{e}$(t). The winter and summer models are shown by equations (D3) and (D4) respectively.

$$(1 - 0.842B)\tilde{e}(t) = a(t) \qquad (D3)$$

and

$$(1 - 1.201B - 0.466B^2)\tilde{e}(t) = a(t) \qquad (D4)$$

Transfer function anlysis (TF)

The TF time series models were also identified and their parameters estimated using four weeks of data in each season. The input variables that were used with these models are: (1) dry bulb temperature, x(t), with the daily peak models & (2) average of daily dry bulb temperature with the energy models. These are modeled as centered series as follows:

(i) winter daily peak

$$\tilde{y}(t) = (-38.27 + 20.87B + 18.24B^2)\,\tilde{x}(t) + \frac{a(t)}{(1 + 0.294B^2)(1 - 0.745B^7)} \tag{D5}$$

(ii) summer daily peak

$$\tilde{y}(t) = 133.43\,\tilde{x}(t) + \frac{a(t)}{(1 - 769B)(1 - 0.813B^7)} \tag{D6}$$

(iii) winter daily energy

$$\tilde{e}(t) = 120.75\,\tilde{x}(t) + \frac{a(t)}{(1 - 0.778B)(1 - 0.799B^7)} \tag{D7}$$

(iv) summer daily energy

$$\tilde{e}(t) = (-43.96 + 26.49B)\tilde{x}(t) + \frac{a(t)}{(1 - 0.907B^7)} \tag{D8}$$

Linear regression analysis (LR)

Multiple linear regression was used to develop models for the daily peak and energy using weather input(s)--both current and time-delayed (lag) responses. Like the other two models the database for these models is four-week long. These models are presented for the daily energy (for summer and winter seasons). Similar models for the daily peak were developed.

For the winter season the daily energy model, e(t), was developed using the average daily dry bulb temperature, T(t), with the day type history as:

$$e(t) \;=\; 4358 + 0.574\, e(t-7) - 80.98\, T(t) + 28.29\, T(t-7) \qquad (D9)$$

The summer daily energy model was developed using the dry bulb temperature (DBT) and the dew point temperature (DPT) which form the temperature humidity index (THI) as shown below. The temperatures are in degree Fahrenheit.

$$THI = 0.55 \times DBT + 0.2 \times DPT + 17.5 \qquad (D10)$$

Using this index, the summer daily energy model can be expressed as:

$$e(t) \;=\; 0.672\, e(t-7) \;+\; 153.27\, THI(t) + 36.70\, THI(t-1) \;-\; 161.63\, THI(t-7) \qquad (D11)$$

Appendix E

DAILY PEAK PREDICTIONS USING ALL MODELS

This Appendix contains the results of the models discussed in sections 9.4.1 through 9.4.3. The results are for the daily peak for both the one day and the seven day ahead predictions using all 15 models.

Table 44. One-Day Lead Time Daily Peak Forecast Error Using Hourly Load Univariate Model

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	23.79	.36	146.73	3.13	122.71	1.50	-102.89	-2.14
2	-432.60	-7.19	403.32	7.29	342.99	4.18	-158.61	-3.44
3	363.67	5.89	126.34	2.33	-27.00	-.33	593.11	10.45
4	416.88	6.10	-328.64	-6.34	129.36	1.57	361.60	6.12
5	-103.60	-1.59	98.94	1.93	226.65	2.76	312.01	5.17
6	537.74	8.32	56.47	1.11	-100.74	-1.32	-202.77	-3.64
7	-92.68	-1.34	-129.24	-2.86	-471.23	-6.33	-64.61	-1.25
8	-7.31	-.10	-298.08	-6.87	904.61	10.36	-328.42	-6.83
9	261.38	3.54	217.74	4.21	63.59	.72	-340.63	-7.55
10	49.34	.68	-19.50	-.37	53.18	.67	71.93	1.35
11	72.83	.97	89.12	1.73	633.22	7.10	172.65	3.08
12	-418.29	-6.28	33.47	.66	-1196.75	-17.30	144.42	2.49
13	-73.58	-1.13	-7.26	-.15	-1780.06	-35.41	375.56	6.25
14	-188.35	-2.69	35.72	.76	-1118.74	-24.13	-488.94	-9.36
15	-443.80	-6.58	86.44	1.80	-401.35	-6.93	-174.43	-3.70
16	4.71	.07	233.62	4.28	42.58	.68	-222.60	-4.84
17	-112.64	-1.77	48.61	.93	754.50	10.35	261.40	4.85
18	-182.37	-2.79	33.06	.65	13.71	.18	79.70	1.45
19	-48.89	-.85	-2.74	-.05	1010.47	11.89	115.99	2.08
20	-177.28	-3.24	339.54	6.40	1729.40	19.81	-25.40	-.45
21	-92.47	-1.48	-281.62	-5.64	-940.76	-12.51	267.86	4.84
22	170.25	2.76	-146.21	-3.11	2237.57	23.79	-384.36	-7.74
23	27.84	.47	524.12	9.18	-1116.06	-14.06	-46.11	-.96
24	54.10	.86	-93.29	-1.75	-286.02	-3.88	233.09	4.28
25	226.49	3.45	73.43	1.41	13.94	.20	239.27	4.20
26	461.06	7.30	120.27	2.27	-54.68	-.78	-180.33	-3.22
27	-212.71	-3.69	-316.47	-6.21	234.35	3.10	168.48	2.88
28	328.99	4.87	-231.98	-5.28	-513.33	-7.33	-	-
29	-	-	-221.32	-5.23	59.06	.75	-	-
30	-	-	-167.44	-3.51	1182.65	14.61	-	-
31	-	-	819.37	14.72	45.46	.60	-	-
Av	199.49	3.08	184.84	3.62	574.41	7.90	226.56	4.24

Table 45. One-Day Lead Time Daily Peak Forecast Error Using Hourly Load Transfer Function Model with Actual Future Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-183.29	-2.79	253.18	5.41	64.92	.80	-105.16	-2.19
2	-243.24	-4.04	592.54	10.71	284.29	3.46	-183.36	-3.98
3	109.98	1.78	-148.30	-2.73	-66.84	-.82	580.07	10.22
4	257.75	3.77	-704.99	-13.60	79.80	.97	366.04	6.20
5	164.86	2.53	130.15	2.54	185.38	2.26	245.95	4.07
6	937.09	14.49	-212.41	-4.18	-139.16	-1.83	-1.40	-.03
7	-279.99	-4.05	113.52	2.51	-486.39	-6.54	-9.92	-.19
8	-302.36	-4.25	-298.52	-6.88	889.52	10.19	-396.52	-8.25
9	386.30	5.24	-241.48	-4.67	70.69	.81	-354.74	-7.86
10	-214.42	-2.95	79.31	1.51	8.13	.10	86.06	1.61
11	-66.63	-.89	240.37	4.67	633.92	7.11	26.42	.47
12	-263.27	-3.95	-22.34	-.44	-1210.29	-17.50	172.60	2.97
13	235.40	3.60	148.16	2.96	-1780.83	-35.43	298.73	4.97
14	-157.06	-2.24	35.86	.76	-1091.19	-23.53	-170.48	-3.26
15	-733.98	-10.89	-49.82	-1.04	-418.86	-7.23	-235.99	-5.00
16	100.74	1.52	43.98	.80	6.08	.10	-279.64	-6.09
17	-213.97	-3.35	-162.25	-3.10	730.56	10.02	197.16	3.66
18	-465.44	-7.11	-18.56	-.37	-23.98	-.31	122.51	2.23
19	11.66	.20	135.91	2.67	1007.86	11.86	170.92	3.07
20	70.37	1.29	311.47	5.87	1704.08	19.52	-39.93	-.71
21	-28.13	-.45	-489.66	-9.80	-918.68	-12.21	220.13	3.97
22	-34.81	-.56	-82.68	-1.76	2182.69	23.21	-445.39	-8.96
23	230.49	3.87	620.54	10.87	-1150.73	-14.49	-158.18	-3.28
24	-218.77	-3.46	-550.77	-10.35	-244.72	-3.32	400.93	7.36
25	246.86	3.76	108.35	2.08	12.00	.17	323.70	5.68
26	287.02	4.54	-23.20	-.44	-47.30	-.67	-127.39	-2.28
27	22.30	.39	-717.82	-14.07	214.81	2.84	189.64	3.24
28	556.38	8.23	11.51	.26	-542.28	-7.74	-	-
29	-	-	-32.40	-.77	77.01	.98	-	-
30	-	-	-324.56	-6.81	1193.53	14.74	-	-
31	-	-	896.63	16.11	37.96	.50	-	-
Av	250.81	3.79	251.65	4.86	564.66	7.78	218.85	4.14

Table 46. One-Day Lead Time Daily Peak Forecast Error Using Hourly Load Transfer Function Model with Predicted Future Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-162.89	-2.48	134.45	2.87	30.68	.38	-81.18	-1.69
2	-390.77	-6.49	363.56	6.57	327.22	3.98	-123.38	-2.68
3	650.54	10.54	173.02	3.19	-76.75	-.94	623.26	10.98
4	-45.72	-.67	-740.03	-14.28	95.63	1.16	321.33	5.44
5	-437.63	-6.73	-384.22	-7.51	174.72	2.13	238.98	3.96
6	809.49	12.52	667.45	13.13	-127.61	-1.67	-173.74	-3.12
7	172.24	2.49	-458.50	-10.16	-512.85	-6.89	136.65	2.65
8	-167.37	-2.35	286.61	6.61	900.98	10.32	-434.38	-9.03
9	209.28	2.84	-237.07	-4.59	13.42	.15	-431.44	-9.56
10	336.69	4.62	-193.51	-3.69	48.76	.61	122.57	2.29
11	-253.56	-3.39	397.15	7.72	600.04	6.73	217.35	3.88
12	-678.31	-10.18	291.72	5.75	-1204.80	-17.42	91.33	1.57
13	247.34	3.78	-359.50	-7.18	-1775.59	-35.32	385.11	6.41
14	167.90	2.39	443.09	9.44	-1096.18	-23.64	-507.76	-9.72
15	-557.97	-8.28	-140.59	-2.93	-416.59	-7.19	127.05	2.69
16	-128.00	-1.93	369.70	6.77	20.05	.32	-323.62	-7.04
17	-9.78	-.15	-604.74	-11.56	712.93	9.78	199.97	3.71
18	-342.39	-5.23	560.38	11.06	-49.87	-.65	35.91	.65
19	-360.03	-6.26	-182.31	-3.58	993.53	11.69	95.55	1.72
20	55.55	1.02	647.63	12.21	1732.02	19.84	80.39	1.43
21	212.31	3.40	-573.40	-11.48	-1021.70	-13.58	243.74	4.40
22	246.00	3.98	-279.84	-5.96	2307.03	24.53	-434.06	-8.74
23	-95.88	-1.61	583.89	10.23	-1216.37	-15.32	-73.70	-1.53
24	-60.51	-.96	229.77	4.32	-218.32	-2.96	163.39	3.00
25	57.60	.88	-549.94	-10.54	33.80	.48	487.95	8.57
26	260.85	4.13	368.59	6.96	-55.42	-.79	-82.89	-1.48
27	-71.98	-1.25	-578.02	-11.33	206.64	2.74	116.06	1.98
28	555.19	8.21	-191.03	-4.35	-538.89	-7.69	-	-
29	-	-	195.53	4.62	61.21	.78	-	-
30	-	-	-309.43	-6.49	1211.12	14.96	-	-
31	-	-	764.64	13.74	24.48	.32	-	-
Av	276.56	4.24	395.46	7.77	574.36	7.90	235.29	4.44

Table 47. One-Week Lead Time Daily Peak Forecast Error Using Hourly Load Univariate Model

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	451.51	6.88	295.10	6.30	2527.94	30.98	1621.26	33.73
2	-373.41	-6.20	3194.62	57.75	1746.83	21.27	-30.95	-.67
3	-303.36	-4.92	2698.17	49.69	2471.11	30.22	3670.83	64.67
4	-163.89	-2.40	1110.53	21.42	-253.65	-3.09	-291.35	-4.93
5	657.94	10.11	292.93	5.72	-60.36	-.74	874.30	14.48
6	1163.53	18.00	-69.39	-1.37	-1537.52	-20.18	510.76	9.16
7	756.49	10.96	-249.00	-5.52	-1081.73	-14.54	540.91	10.49
8	1171.27	16.48	-21.77	-.50	1008.69	11.55	-916.78	-19.06
9	2069.05	28.06	-961.40	-18.60	-133.59	-1.52	-350.15	-7.76
10	1298.02	17.83	-743.48	-14.17	-587.66	-7.38	-974.81	-18.24
11	217.94	2.91	1443.70	28.08	2960.06	33.19	277.98	4.96
12	168.38	2.53	-36.23	-.71	-937.84	-13.56	-130.56	-2.25
13	125.06	1.91	1057.95	21.13	-2802.05	-55.74	1059.80	17.63
14	-90.54	-1.29	-940.20	-20.03	-3192.16	-68.84	-457.14	-8.75
15	-515.67	-7.65	987.15	20.58	-2922.54	-50.46	-999.45	-21.19
16	-874.41	-13.16	-553.11	-10.12	-780.21	-12.38	-520.23	-11.32
17	-1022.27	-16.02	1164.22	22.26	-1850.71	-25.38	441.18	8.18
18	-1212.96	-18.54	-339.74	-6.71	-510.86	-6.62	210.24	3.83
19	-1270.57	-22.09	211.38	4.16	1980.11	23.30	-724.38	-13.00
20	-1196.65	-21.90	371.75	7.01	4728.99	54.16	-1010.25	-17.92
21	-820.40	-13.14	-359.08	-7.19	2631.38	34.98	965.02	17.42
22	-291.33	-4.72	-72.55	-1.55	5009.11	53.27	-1590.18	-32.00
23	-446.14	-7.49	329.32	5.77	2919.48	36.77	-15.20	-.32
24	-67.69	-1.07	477.88	8.98	23.48	.32	1163.91	21.36
25	440.58	6.71	901.73	17.28	-1483.50	-20.98	1033.25	18.15
26	710.04	11.24	1650.53	31.16	-249.67	-3.56	-1.54	-.03
27	342.79	5.94	-3258.87	-63.90	-4916.35	-65.10	615.51	10.52
28	1039.16	15.37	-975.10	-22.19	423.70	6.05	-	-
29	-	-	-890.95	-21.07	-3560.28	-45.18	-	-
30	-	-	-228.14	-4.78	328.53	4.06	-	-
31	-	-	-508.02	-9.13	891.12	11.67	-	-
Av	687.90	10.55	851.42	16.61	1822.94	24.74	777.70	14.52

Table 48. One-Week Lead Time Daily Peak Forecast Error Using Hourly Load Transfer Function Model with Actual Future Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	388.57	5.93	-1009.75	-21.56	1707.94	20.93	1770.51	36.84
2	-.94	-.02	4674.94	84.51	559.01	6.81	-626.50	-13.60
3	-385.46	-6.25	3512.52	64.69	1407.76	17.22	3318.11	58.46
4	-682.96	-10.00	1285.87	24.80	-1308.06	-15.91	-497.84	-8.43
5	223.33	3.43	-5.45	-.11	-879.68	-10.73	791.29	13.11
6	1270.89	19.66	-531.19	-10.45	-2277.43	-29.89	408.30	7.32
7	1056.32	15.30	-454.45	-10.07	-1839.80	-24.72	1044.56	20.25
8	973.21	13.69	113.11	2.61	186.53	2.14	-869.54	-18.08
9	1669.12	22.64	-3195.32	-61.82	-695.43	-7.93	120.25	2.67
10	1460.48	20.06	-1901.50	-36.23	-1048.37	-13.17	-797.08	-14.92
11	584.83	7.82	1483.31	28.85	2529.04	28.36	366.16	6.54
12	-113.84	-1.71	214.10	4.22	-1419.52	-20.53	-180.98	-3.12
13	-196.63	-3.01	1535.02	30.66	-3105.12	-61.77	661.47	11.01
14	404.44	5.77	-481.32	-10.26	-3495.02	-75.37	-596.56	-11.42
15	-284.35	-4.22	877.36	18.29	-3116.57	-53.81	-1085.15	-23.01
16	-1101.73	-16.58	1775.59	32.50	-1076.83	-17.09	-228.93	-4.98
17	-916.49	-14.37	1716.17	32.81	-2132.36	-29.25	158.92	2.95
18	-1094.05	-16.72	-916.79	-18.10	-974.40	-12.63	488.44	8.90
19	-1403.93	-24.41	399.93	7.86	1724.64	20.29	-330.63	-5.93
20	-1493.85	-27.34	-146.04	-2.75	4406.42	50.46	-198.62	-3.52
21	-752.72	-12.06	-874.34	-17.50	2369.56	31.50	394.90	7.13
22	-91.33	-1.48	-82.06	-1.75	4639.07	49.33	-1589.05	-31.98
23	-358.54	-6.02	303.06	5.31	2742.89	34.55	-368.34	-7.64
24	-224.17	-3.55	596.68	11.21	-145.52	-1.98	1192.94	21.90
25	602.61	9.18	1114.40	21.36	-1557.04	-22.02	914.47	16.06
26	447.82	7.09	793.76	14.99	-460.18	-6.56	58.92	1.05
27	-24.84	-.43	-4001.94	-78.47	-4987.54	-66.04	744.73	12.73
28	1110.46	16.43	-1488.40	-33.87	220.79	3.15	-	-
29	-	-	-888.93	-21.02	-3733.20	-47.37	-	-
30	-	-	-1412.09	-29.61	319.40	3.95	-	-
31	-	-	280.13	5.03	749.67	9.82	-	-
Av	689.93	10.54	1227.92	23.98	1864.99	25.65	733.45	13.84

Table 49. One-Week Lead Time Daily Peak Forecast Error Using Hourly Load Transfer Function Model with Predicted Future Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	670.03	10.22	342.44	7.31	1407.49	17.25	1203.47	25.04
2	-361.65	-6.01	3380.74	61.11	557.52	6.79	-617.59	-13.41
3	-479.62	-7.77	1733.43	31.92	1286.41	15.73	3541.41	62.39
4	-329.25	-4.82	2505.31	48.33	-979.48	-11.91	-641.92	-10.87
5	491.80	7.56	-1280.02	-25.01	-997.62	-12.16	1510.47	25.02
6	1336.48	20.67	-258.46	-5.09	-2364.87	-31.04	440.35	7.90
7	649.01	9.40	-1591.41	-35.25	-2069.82	-27.81	970.18	18.81
8	1286.65	18.10	-841.61	-19.41	871.05	9.98	-393.15	-8.18
9	2149.28	29.15	-802.92	-15.53	-714.67	-8.15	-343.90	-7.62
10	1081.04	14.85	-3651.68	-69.58	-997.19	-12.53	-880.63	-16.48
11	199.74	2.67	-2476.76	-48.17	2240.56	25.12	-289.04	-5.16
12	301.39	4.52	5074.00	100.00	-1236.14	-17.87	154.82	2.67
13	170.30	2.60	-2241.93	-44.78	-3409.37	-67.82	2557.82	42.56
14	-228.16	-3.25	3697.17	78.78	-3286.02	-70.87	-1480.90	-28.35
15	-432.88	-6.42	-2000.28	-41.71	-3606.94	-62.27	-1471.31	-31.20
16	-787.93	-11.86	-892.69	-16.34	-769.93	-12.22	-93.21	-2.03
17	-1251.88	-19.62	3410.93	65.21	-2289.32	-31.40	606.03	11.24
18	-1264.82	-19.33	1786.45	35.27	-512.78	-6.64	-276.64	-5.04
19	-1131.87	-19.68	-2762.61	-54.32	1932.56	22.74	-644.99	-11.58
20	-1155.38	-21.15	3303.59	62.28	4748.49	54.38	-1121.14	-19.89
21	-971.40	-15.56	-2585.16	-51.74	2272.88	30.22	2954.26	53.33
22	-254.90	-4.13	1086.93	23.16	4629.98	49.23	-2302.11	-46.33
23	-538.35	-9.03	-6165.78	-108.02	2395.85	30.17	-579.72	-12.03
24	-113.14	-1.79	5322.00	100.00	-683.17	-9.27	1099.06	20.17
25	442.57	6.74	-1263.83	-24.23	-1660.43	-23.48	744.08	13.07
26	951.31	15.05	4409.80	83.25	-46.23	-.66	460.96	8.24
27	439.88	7.62	-6111.72	-119.84	-5828.66	-77.18	75.02	1.28
28	917.04	13.57	-1481.59	-33.71	1606.47	22.94	-	-
29	-	-	554.51	13.12	-4686.13	-59.46	-	-
30	-	-	1922.59	40.31	1291.77	15.96	-	-
31	-	-	-6159.48	-110.66	1032.48	13.52	-	-
Av	728.13	11.18	2616.06	50.76	2013.30	27.64	1016.82	18.88

Table 50. One-Day Lead Time Daily Peak Forecast Error Using Daily Peak Univariate Model

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	182.19	2.78	67.59	1.44	458.73	5.62	-659.32	-13.72
2	-832.17	-13.83	-38.50	-.70	183.07	2.23	-479.12	-10.40
3	174.06	2.82	119.06	2.19	101.72	1.24	757.36	13.34
4	447.50	6.55	6.68	.13	175.56	2.14	103.59	1.75
5	160.57	2.47	-165.61	-3.24	121.07	1.48	47.87	.79
6	483.33	7.48	66.15	1.30	-445.61	-5.85	-520.80	-9.34
7	-106.38	-1.54	-226.58	-5.02	-154.23	-2.07	-560.08	-10.86
8	165.60	2.33	-284.09	-6.55	1279.32	14.65	-564.93	-11.75
9	734.35	9.96	46.08	.89	279.96	3.19	-574.59	-12.73
10	5.93	.08	75.00	1.43	-568.11	-7.14	500.93	9.38
11	-89.32	-1.19	41.40	.81	1050.18	11.77	75.76	1.35
12	-463.51	-6.96	-39.70	-.78	-1727.85	-24.98	67.52	1.16
13	-75.32	-1.15	-67.17	-1.34	-2001.47	-39.81	101.74	1.69
14	171.74	2.45	92.58	1.97	-868.03	-18.72	-851.40	-16.30
15	-376.77	-5.59	236.67	4.93	601.50	10.39	-712.27	-15.10
16	-319.41	-4.81	73.48	1.34	179.01	2.84	-415.02	-9.03
17	-287.15	-4.50	-235.24	-4.50	758.51	10.40	481.60	8.93
18	-99.72	-1.52	-96.86	-1.91	386.10	5.00	-78.59	-1.43
19	-341.33	-5.94	39.92	.78	823.54	9.69	-74.63	-1.34
20	-357.79	-6.55	255.21	4.81	427.68	4.90	-75.96	-1.35
21	257.12	4.12	-12.88	-.26	-971.04	-12.91	-229.12	-4.14
22	7.29	.12	-346.92	-7.39	1886.80	20.06	-719.44	-14.48
23	-243.06	-4.08	434.26	7.61	-1095.00	-13.79	-398.32	-8.26
24	423.34	6.70	-141.60	-2.66	-488.31	-6.63	352.35	6.47
25	108.65	1.66	36.67	.70	-319.39	-4.52	81.31	1.43
26	306.76	4.85	81.95	1.55	-134.28	-1.91	-220.23	-3.94
27	-293.81	-5.09	-332.86	-6.53	439.65	5.82	115.28	1.97
28	438.69	6.49	-521.59	-11.87	-537.39	-7.67	-	-
29	-	-	-103.17	-2.44	781.56	9.92	-	-
30	-	-	-403.92	-8.47	288.27	3.56	-	-
31	-	-	881.59	15.84	-344.31	-4.51	-	-
Av	284.03	4.41	179.71	3.59	641.20	8.88	363.67	7.13

Table 51. One-Day Lead Time Daily Peak Forecast Error Using Daily Peak Transfer Function Model with Actual Future Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	137.48	2.10	334.65	7.14	-275.00	-3.37	-1119.86	-23.30
2	-181.49	-3.02	174.66	3.16	850.34	10.35	-772.65	-16.78
3	176.37	2.86	89.18	1.64	-34.77	-.43	-133.70	-2.36
4	-1.99	-.03	-279.94	-5.40	385.82	4.69	-512.08	-8.67
5	-89.67	-1.38	-290.14	-5.67	-200.66	-2.45	-184.99	-3.06
6	132.66	2.05	-100.47	-1.98	73.96	.97	-150.55	-2.70
7	243.98	3.53	-140.51	-3.11	-.25	-.00	-329.63	-6.39
8	238.88	3.36	-349.14	-8.05	621.41	7.12	-694.48	-14.44
9	346.76	4.70	-359.79	-6.96	-708.61	-8.08	-834.18	-18.49
10	-6.10	-.08	-81.08	-1.54	463.81	5.83	630.01	11.79
11	136.03	1.82	175.91	3.42	-540.20	-6.06	153.73	2.74
12	-193.97	-2.91	-26.68	-.53	70.16	1.01	-558.08	-9.61
13	-14.17	-.22	111.01	2.22	-132.66	-2.64	-323.04	-5.38
14	113.61	1.62	134.02	2.86	-744.40	-16.05	-17.60	-.34
15	121.81	1.81	500.34	10.43	-549.58	-9.49	-781.66	-16.57
16	-264.03	-3.97	225.30	4.12	133.14	2.11	-428.18	-9.32
17	-212.84	-3.34	-272.06	-5.20	-146.04	-2.00	212.71	3.94
18	151.48	2.32	-55.88	-1.10	273.75	3.55	-121.05	-2.21
19	-270.43	-4.70	20.52	.40	796.12	9.37	889.74	15.97
20	-325.28	-5.95	359.84	6.78	-604.20	-6.92	370.14	6.57
21	492.77	7.89	35.29	.71	985.28	13.10	297.63	5.37
22	141.07	2.28	-436.94	-9.31	209.52	2.23	-536.62	-10.80
23	-524.40	-8.80	796.47	13.95	718.75	9.05	-457.13	-9.48
24	234.93	3.72	44.03	.83	-295.35	-4.01	338.95	6.22
25	-99.17	-1.51	141.87	2.72	-253.96	-3.59	805.91	14.15
26	162.93	2.58	282.20	5.33	-949.65	-13.53	209.92	3.75
27	-69.05	-1.20	-449.39	-8.81	279.21	3.70	730.32	12.49
28	430.98	6.38	-512.82	-11.67	-120.39	-1.72	-	-
29	-	-	-225.22	-5.33	500.28	6.35	-	-
30	-	-	-573.48	-12.03	-74.16	-.92	-	-
31	-	-	852.53	15.32	-368.55	-4.83	-	-
Av	196.94	3.08	271.98	5.41	398.71	5.34	466.46	9.00

Table 52. One-Day Lead Time Daily Peak Forecast Error Using Daily Peak Transfer Function Model with Predicted Future Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-5.90	-.09	82.61	1.76	-895.55	-10.98	-91.50	-1.90
2	-789.42	-13.12	169.61	3.07	481.84	5.87	-1007.49	-21.88
3	527.47	8.55	420.49	7.74	235.76	2.88	492.93	8.68
4	385.02	5.63	180.91	3.49	103.06	1.25	60.34	1.02
5	40.80	.63	-486.63	-9.51	381.15	4.65	-209.59	-3.47
6	437.69	6.77	-350.61	-6.90	-608.91	-7.99	-788.16	-14.13
7	-18.36	-.27	-501.37	-11.11	18.85	.25	-149.80	-2.90
8	266.03	3.74	-290.45	-6.70	1008.99	11.56	-288.60	-6.00
9	750.71	10.18	-95.06	-1.84	135.96	1.55	-721.70	-16.00
10	-201.93	-2.77	-376.19	-7.17	-1225.33	-15.40	343.69	6.43
11	35.84	.48	-340.93	-6.63	1650.44	18.50	285.60	5.10
12	-424.56	-6.37	-155.48	-3.06	-2835.65	-41.00	79.21	1.36
13	-59.01	-.90	176.33	3.52	-457.87	-9.11	-204.27	-3.40
14	68.90	.98	-48.32	-1.03	378.21	8.16	-906.77	-17.36
15	-61.30	-.91	490.49	10.23	-148.75	-2.57	131.21	2.78
16	-470.39	-7.08	300.29	5.50	-582.29	-9.24	-443.41	-9.65
17	-260.89	-4.09	-17.74	-.34	1490.48	20.44	553.52	10.27
18	-21.54	-.33	-219.80	-4.34	-1495.50	-19.38	-11.35	-.21
19	-348.55	-6.06	227.95	4.48	3058.14	35.99	17.85	.32
20	-424.97	-7.78	282.80	5.33	921.74	10.56	620.69	11.01
21	116.08	1.86	211.45	4.23	-2061.04	-27.40	214.96	3.88
22	-363.74	-5.89	-385.66	-8.22	1970.38	20.95	-71.42	-1.44
23	-111.15	-1.87	353.01	6.18	-1740.57	-21.92	-148.48	-3.08
24	634.34	10.04	331.04	6.22	152.62	2.07	14.09	.26
25	-305.52	-4.66	238.34	4.57	-79.62	-1.13	372.12	6.54
26	437.61	6.93	229.40	4.33	-816.48	-11.63	705.19	12.60
27	-371.99	-6.44	-144.72	-2.84	147.57	1.95	518.50	8.86
28	457.44	6.77	-761.07	-17.32	493.23	7.04	-	-
29	-	-	-368.27	-8.71	-1059.08	-13.44	-	-
30	-	-	-455.87	-9.56	1993.42	24.63	-	-
31	-	-	490.73	8.82	-759.02	-9.94	-	-
Av	299.90	4.68	296.25	5.96	947.98	12.24	350.09	6.69

Table 53. One-Week Lead Time Daily Peak Forecast Error Using Daily Peak Univariate Model

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	363.71	5.55	-308.85	-6.59	731.53	8.97	-1139.71	-23.71
2	-541.50	-9.00	-263.29	-4.76	772.11	9.40	-1296.60	-28.16
3	-197.49	-3.20	-3.82	-.07	654.11	8.00	-414.08	-7.30
4	172.35	2.52	76.01	1.47	653.51	7.95	-209.67	-3.55
5	317.18	4.88	-130.09	-2.54	644.50	7.86	-92.29	-1.53
6	833.62	12.89	-33.01	-.65	66.27	.87	-520.49	-9.33
7	472.56	6.84	-226.54	-5.02	-111.07	-1.49	-937.21	-18.17
8	508.01	7.15	-463.91	-10.70	1087.95	12.46	-1167.48	-24.28
9	1368.18	18.55	-297.91	-5.76	1116.75	12.73	-1412.94	-31.32
10	1088.67	14.95	-165.60	-3.16	309.96	3.89	-856.58	-16.03
11	692.34	9.26	-84.19	-1.64	1261.20	14.14	-656.04	-11.71
12	65.65	.99	-80.38	-1.58	-737.59	-10.66	-484.89	-8.35
13	-146.14	-2.24	-136.76	-2.73	-2497.44	-49.68	-163.93	-2.73
14	78.79	1.12	20.68	.44	-2847.94	-61.42	-842.74	-16.13
15	-354.63	-5.26	291.19	6.07	-1979.20	-34.17	-1261.25	-26.74
16	-801.53	-12.06	286.38	5.24	-1479.29	-23.48	-1306.09	-28.42
17	-949.34	-14.88	-29.91	-.57	-308.44	-4.23	-722.18	-13.39
18	-859.13	-13.13	-125.05	-2.47	-95.69	-1.24	-692.60	-12.62
19	-929.67	-16.17	-48.79	-.96	1129.78	13.29	-662.17	-11.89
20	-1104.60	-20.22	227.69	4.29	1782.95	20.42	-647.22	-11.48
21	-697.75	-11.18	145.85	2.92	659.49	8.77	-543.67	-9.81
22	-470.44	-7.62	-269.56	-5.74	2285.19	24.30	-984.40	-19.81
23	-548.26	-9.20	221.25	3.88	708.25	8.92	-1102.37	-22.87
24	45.65	.72	57.22	1.08	-85.44	-1.16	-678.75	-12.46
25	172.06	2.62	93.03	1.78	-473.97	-6.70	-457.37	-8.03
26	536.80	8.50	146.52	2.77	-699.27	-9.96	-577.65	-10.32
27	241.13	4.18	-257.54	-5.05	-219.20	-2.90	-340.83	-5.83
28	570.99	8.45	-713.71	-16.24	-498.70	-7.12	-	-
29	-	-	-592.94	-14.02	-39.31	-.50	-	-
30	-	-	-909.85	-19.08	499.55	6.17	-	-
31	-	-	216.01	3.88	166.92	2.19	-	-
Av.	540.29	8.33	223.34	4.62	858.15	12.42	747.08	14.67

Table 54. One-Week Lead Time Load Forecast Error Using Daily Peak Load Transfer Function Model with Actual Future Input data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	373.76	5.70	377.16	8.05	-317.11	-3.89	-1201.76	-25.01
2	45.74	.76	342.04	6.18	676.29	8.23	-1456.08	-31.62
3	217.09	3.52	241.46	4.45	553.47	6.77	-1000.33	-17.62
4	126.21	1.85	-171.95	-3.32	829.41	10.09	-1089.57	-18.45
5	-5.16	-.08	-368.59	-7.20	386.69	4.71	-829.62	-13.74
6	129.57	2.00	-265.55	-5.23	356.43	4.68	-645.40	-11.57
7	312.82	4.53	-258.65	-5.73	273.00	3.67	-712.99	-13.82
8	435.88	6.13	-465.69	-10.74	875.04	10.02	-1088.48	-22.63
9	639.89	8.68	-568.14	-10.99	-170.91	-1.95	-1459.88	-32.36
10	402.11	5.52	-334.82	-6.38	337.92	4.25	-232.51	-4.35
11	398.19	5.32	27.53	.54	-341.68	-3.83	29.05	.52
12	70.01	1.05	-13.38	-.26	-160.68	-2.32	-536.07	-9.23
13	24.83	.38	105.39	2.11	-267.98	-5.33	-637.13	-10.60
14	117.61	1.68	181.52	3.87	-950.42	-20.50	-387.02	-7.41
15	186.52	2.77	582.54	12.15	-1379.18	-23.81	-993.28	-21.06
16	-159.78	-2.40	486.41	8.90	-814.74	-12.93	-995.82	-21.67
17	-316.66	-4.96	-54.80	-1.05	-846.26	-11.61	-394.27	-7.31
18	-61.68	-.94	-80.94	-1.60	-291.11	-3.77	-358.89	-6.54
19	-300.94	-5.23	-15.50	-.30	561.11	6.60	691.27	12.41
20	-520.70	-9.53	352.54	6.65	-151.64	-1.74	788.54	13.99
21	147.75	2.37	192.08	3.84	987.01	13.12	765.83	13.82
22	231.28	3.74	-353.01	-7.52	1055.84	11.23	-62.15	-1.25
23	-360.49	-6.05	638.21	11.18	1509.48	19.01	-482.93	-10.02
24	10.62	.17	329.68	6.19	888.58	12.06	46.99	.86
25	-99.81	-1.52	289.12	5.54	385.80	5.46	836.91	14.70
26	111.38	1.76	411.10	7.76	-779.55	-11.10	683.37	12.21
27	19.78	.34	-267.27	-5.24	-224.18	-2.97	1126.12	19.25
28	419.27	6.20	-632.16	-14.38	-449.40	-6.42	-	-
29	-	-	-505.68	-11.96	121.41	1.54	-	-
30	-	-	-801.85	-16.81	-95.05	-1.17	-	-
31	-	-	494.70	8.89	-394.69	-5.17	-	-
AV.	223.05	3.40	329.34	6.61	562.32	7.74	723.42	13.85

Table 55. One-Week Lead Time Daily Peak Forecast Error Using Daily Peak Transfer Function Model with Predicted Future Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-79.71	-1.22	-335.30	-7.16	225.94	2.77	-1072.66	-22.32
2	-892.04	-14.82	-296.34	-5.36	462.67	5.63	-1339.71	-29.09
3	-370.81	-6.01	-.92	-.02	483.07	5.91	-418.79	-7.38
4	-11.02	-.16	126.51	2.44	538.44	6.55	-285.77	-4.84
5	264.31	4.06	-392.58	-7.67	695.40	8.48	-96.60	-1.60
6	751.12	11.62	-275.92	-5.43	-215.05	-2.82	-463.82	-8.32
7	395.81	5.73	-618.34	-13.70	-201.02	-2.70	-717.48	-13.91
8	589.98	8.30	-690.46	-15.92	1193.20	13.66	-1330.37	-27.66
9	1260.47	17.09	-502.38	-9.72	853.14	9.72	-1646.17	-36.48
10	767.30	10.54	-398.41	-7.59	-137.74	-1.73	-874.21	-16.36
11	452.53	6.05	-344.09	-6.69	847.48	9.50	-737.99	-13.17
12	92.30	1.39	-313.82	-6.18	-1310.15	-18.94	-613.06	-10.56
13	62.25	.95	-136.75	-2.73	-2581.39	-51.35	-153.60	-2.56
14	175.04	2.50	-3.62	-.08	-2824.65	-60.92	-818.04	-15.66
15	-203.71	-3.02	111.12	2.32	-2719.35	-46.95	-1376.61	-29.19
16	-500.67	-7.53	10.22	.19	-2417.55	-38.37	-1495.35	-32.54
17	-571.53	-8.96	-114.92	-2.20	-78.93	-1.08	-659.57	-12.23
18	-646.81	-9.89	-68.43	-1.35	-1459.80	-18.92	-634.09	-11.55
19	-700.74	-12.18	50.77	1.00	2391.69	28.14	-722.16	-12.96
20	-916.59	-16.78	96.32	1.82	3145.50	36.02	-674.65	-11.97
21	-466.57	-7.47	246.72	4.94	1262.64	16.79	-367.32	-6.63
22	-583.95	-9.45	-436.16	-9.29	2247.93	23.90	-1002.69	-20.18
23	-584.16	-9.80	-24.49	-.43	961.62	12.11	-1128.63	-23.42
24	-40.79	-.65	-192.07	-3.61	-562.89	-7.64	-581.24	-10.67
25	-107.09	-1.63	186.31	3.57	-457.85	-6.47	-367.88	-6.46
26	296.68	4.70	90.69	1.71	-1767.20	-25.17	-270.53	-4.84
27	-47.91	-.83	-342.72	-6.72	-1380.46	-18.28	-15.63	-.27
28	385.50	5.70	-789.87	-17.97	311.32	4.44	-	-
29	-	-	-812.41	-19.21	-1485.19	-18.85	-	-
30	-	-	-934.37	-19.59	1094.34	13.52	-	-
31	-	-	-126.44	-2.27	-62.02	-.81	-	-
Av	436.34	6.75	292.56	6.09	1173.41	16.72	735.73	14.55

Table 56. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Univariate Model and Actual Load Factor

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-15.85	-.24	-223.98	-4.78	747.92	9.17	-717.57	-14.93
2	-532.03	-8.84	140.32	2.54	-54.83	-.67	-554.93	-12.05
3	-157.20	-2.55	296.50	5.46	163.27	2.00	733.10	12.92
4	727.81	10.65	-128.63	-2.48	13.39	.16	69.30	1.17
5	-189.35	-2.91	-69.56	-1.36	32.89	.40	95.49	1.58
6	186.21	2.88	-121.91	-2.40	-420.81	-5.52	-339.89	-6.10
7	165.68	2.40	-127.73	-2.83	-94.00	-1.26	-423.36	-8.21
8	92.33	1.30	-245.05	-5.65	1179.00	13.50	-666.39	-13.86
9	418.77	5.68	52.45	1.01	203.04	2.31	-575.95	-12.76
10	300.70	4.13	-47.13	-.90	-478.28	-6.01	463.39	8.67
11	121.59	1.63	107.38	2.09	745.57	8.36	85.18	1.52
12	-261.84	-3.93	-26.22	-.52	-1206.69	-17.45	106.67	1.84
13	170.66	2.61	-8.45	-.17	-1678.59	-33.39	148.02	2.46
14	355.33	5.07	-80.01	-1.70	-723.73	-15.61	-657.62	-12.59
15	-630.97	-9.36	167.30	3.49	623.99	10.77	-750.00	-15.90
16	-5.89	-.09	116.97	2.14	112.77	1.79	-500.04	-10.88
17	-29.49	-.46	-154.83	-2.96	588.50	8.07	522.24	9.69
18	-450.77	-6.89	-20.26	-.40	652.46	8.45	-93.39	-1.70
19	-256.83	-4.47	41.97	.83	655.70	7.72	-49.00	-.88
20	-270.03	-4.94	203.68	3.84	77.09	.88	-9.59	-.17
21	-10.72	-.17	-42.76	-.86	-548.36	-7.29	-133.91	-2.42
22	-254.21	-4.12	-226.21	-4.82	1221.74	12.99	-644.58	-12.97
23	-93.85	-1.57	446.02	7.81	-285.53	-3.60	-453.70	-9.41
24	124.38	1.97	-79.36	-1.49	-616.31	-8.37	355.67	6.53
25	125.01	1.91	-19.48	-.37	-444.00	-6.28	67.47	1.18
26	-47.50	-.75	26.70	.50	-178.76	-2.55	-105.15	-1.88
27	-294.54	-5.10	-341.90	-6.70	126.01	1.67	130.28	2.23
28	435.42	6.44	-374.51	-8.52	-159.87	-2.28	-	-
29	-	-	-131.94	-3.12	805.87	10.23	-	-
30	-	-	-553.97	-11.62	31.83	.39	-	-
31	-	-	794.56	14.28	-200.90	-2.63	-	-
Av.	240.18	3.68	174.77	3.47	486.18	6.83	350.07	6.91

Table 57. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Actual Input Data and Actual Load Factor

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-178.35	-2.72	83.68	1.79	252.97	3.10	-883.26	-18.38
2	180.17	2.99	547.84	9.90	247.19	3.01	-205.49	-4.46
3	366.85	5.94	474.15	8.73	122.31	1.50	175.55	3.09
4	362.64	5.31	-369.14	-7.12	201.97	2.46	-108.01	-1.83
5	160.15	2.46	-357.48	-6.98	-10.82	-.13	-278.75	-4.62
6	169.20	2.62	-321.66	-6.33	-204.88	-2.69	29.43	.53
7	162.32	2.35	-174.15	-3.86	62.88	.84	166.87	3.24
8	304.53	4.28	-254.99	-5.88	271.72	3.11	211.26	4.39
9	-94.92	-1.29	-616.82	-11.93	-99.17	-1.13	-559.83	-12.41
10	-240.51	-3.30	-407.61	-7.77	63.03	.79	400.73	7.50
11	-98.08	-1.31	196.65	3.82	-164.03	-1.84	277.39	4.95
12	-81.33	-1.22	53.89	1.06	-109.33	-1.58	-415.52	-7.16
13	-98.27	-1.50	142.43	2.85	-214.48	-4.27	-322.85	-5.37
14	128.94	1.84	203.81	4.34	-365.32	-7.88	543.27	10.40
15	-186.66	-2.77	487.09	10.16	-153.51	-2.65	18.12	.38
16	-173.72	-2.61	225.66	4.13	4.10	.07	316.18	6.88
17	-78.98	-1.24	-292.59	-5.59	-33.23	-.46	297.24	5.51
18	-329.45	-5.04	8.78	.17	7.58	.10	-37.15	-.68
19	-178.24	-3.10	137.66	2.71	514.32	6.05	931.10	16.71
20	-308.77	-5.65	468.18	8.83	-34.34	-.39	582.25	10.33
21	-459.63	-7.36	77.05	1.54	352.76	4.69	290.69	5.25
22	-3.55	-.06	-295.28	-6.29	270.88	2.88	-24.16	-.49
23	276.42	4.64	895.60	15.69	388.35	4.89	-503.71	-10.45
24	145.74	2.31	313.99	5.90	-265.20	-3.60	-111.84	-2.05
25	110.62	1.69	64.39	1.23	-110.46	-1.56	1306.19	22.94
26	182.52	2.89	155.66	2.94	-349.70	-4.98	248.10	4.43
27	-20.89	-.36	-596.63	-11.70	-95.02	-1.26	879.25	15.03
28	292.04	4.32	-504.06	-11.47	87.62	1.25	-	-
29	-	-	-149.94	-3.55	108.87	1.38	-	-
30	-	-	-684.05	-14.34	-65.34	-.81	-	-
31	-	-	752.36	13.52	221.75	2.90	-	-
Av	191.91	2.97	332.69	6.52	175.91	2.40	374.97	7.02

Table 58. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Predicted Input Data and Actual Load Factor

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-95.77	-1.46	-8.33	-.18	-241.77	-2.96	-226.41	-4.71
2	-694.53	-11.54	325.94	5.89	237.63	2.89	-769.21	-16.70
3	-8.36	-.14	742.65	13.68	183.94	2.25	486.73	8.58
4	868.81	12.71	114.09	2.20	-94.90	-1.15	-49.37	-.84
5	371.63	5.71	-325.50	-6.36	265.21	3.23	-12.73	-.21
6	446.40	6.90	-396.61	-7.80	-296.69	-3.89	-597.91	-10.72
7	190.56	2.76	-303.07	-6.71	-155.72	-2.09	-147.81	-2.87
8	342.09	4.81	-312.88	-7.22	751.42	8.61	128.33	2.67
9	926.52	12.56	-52.23	-1.01	66.90	.76	124.55	2.76
10	300.38	4.13	-595.97	-11.36	-845.90	-10.63	-197.49	-3.70
11	-236.19	-3.16	-195.49	-3.80	1220.45	13.68	358.20	6.39
12	-15.44	-.23	87.20	1.72	-1814.97	-26.24	277.19	4.77
13	117.17	1.79	64.41	1.29	-631.68	-12.57	-80.97	-1.35
14	125.50	1.79	79.68	1.70	124.60	2.69	-952.19	-18.23
15	-423.00	-6.27	415.13	8.66	-103.74	-1.79	421.91	8.95
16	-432.70	-6.51	399.77	7.32	12.96	.21	135.20	2.94
17	-316.67	-4.96	-19.82	-.38	1000.89	13.73	718.47	13.32
18	-775.02	-11.85	-182.98	-3.61	-595.59	-7.72	-70.68	-1.29
19	-497.58	-8.65	65.62	1.29	1607.25	18.91	-31.08	-.56
20	-517.18	-9.47	306.69	5.78	799.75	9.16	827.11	14.67
21	-646.99	-10.36	268.30	5.37	-977.98	-13.00	802.87	14.49
22	-451.33	-7.31	-146.24	-3.12	924.92	9.84	-150.33	-3.03
23	-16.27	-.27	289.15	5.07	-586.85	-7.39	-21.72	-.45
24	332.10	5.26	453.13	8.51	-494.95	-6.72	-219.92	-4.04
25	253.65	3.87	292.36	5.60	-419.65	-5.93	-40.06	-.70
26	278.94	4.41	88.80	1.68	-113.08	-1.61	993.52	17.76
27	-1.80	-.03	-229.25	-4.50	290.15	3.84	421.15	7.20
28	234.48	3.47	-662.98	-15.08	166.05	2.37	-	-
29			-323.39	-7.65	-231.79	-2.94	-	-
30			-630.95	-13.23	425.94	5.26	-	-
31			599.35	10.77	67.33	.88	-	-
	354.18	5.44	289.61	5.76	508.09	6.61	343.08	6.44

Table 59. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Univariate Model and Actual Load Factor

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-273.89	-4.18	-498.63	-10.65	916.94	11.24	-1071.51	-22.30
2	-634.41	-10.54	-202.82	-3.67	784.23	9.55	-1318.28	-28.63
3	-826.10	-13.39	216.90	3.99	768.01	9.39	-470.52	-8.29
4	95.15	1.39	45.46	.88	603.71	7.34	-292.19	-4.95
5	224.69	3.45	-51.65	-1.01	528.77	6.45	-105.35	-1.75
6	398.97	6.17	-168.88	-3.32	67.58	.89	-373.83	-6.70
7	575.64	8.34	-221.24	-4.90	-79.99	-1.07	-685.31	-13.29
8	595.62	8.38	-386.48	-8.91	876.46	10.04	-1070.57	-22.26
9	812.41	11.02	-230.55	-4.46	959.47	10.94	-1321.42	-29.29
10	973.91	13.38	-237.27	-4.52	266.13	3.34	-795.81	-14.89
11	985.66	13.18	-46.70	-.91	974.14	10.92	-579.17	-10.34
12	415.21	6.23	-52.42	-1.03	-453.13	-6.55	-385.16	-6.63
13	248.16	3.80	-34.96	-.70	-1930.67	-38.41	-82.36	-1.37
14	470.01	6.70	-93.47	-1.99	-2332.91	-50.31	-621.68	-11.90
15	-157.94	-2.34	121.80	2.54	-1742.61	-30.09	-1108.09	-23.50
16	-389.29	-5.86	197.08	3.61	-1456.11	-23.11	-1284.93	-27.96
17	-385.00	-6.03	-13.03	-.25	-532.89	-7.31	-624.03	-11.57
18	-750.55	-11.47	-38.92	-.77	7.96	.10	-624.14	-11.37
19	-973.11	-16.92	16.76	.33	1043.09	12.27	-581.55	-10.44
20	-1064.99	-19.49	216.37	4.08	1557.70	17.84	-514.06	-9.12
21	-857.62	-13.74	120.53	2.41	914.03	12.15	-389.05	-7.02
22	-852.22	-13.80	-155.57	-3.31	1853.57	19.71	-783.25	-15.76
23	-660.69	-11.09	325.57	5.70	1079.55	13.60	-986.38	-20.46
24	-291.56	-4.62	160.34	3.01	142.44	1.93	-574.32	-10.54
25	36.78	.56	95.12	1.82	-520.63	-7.36	-380.46	-6.68
26	114.77	1.82	91.35	1.72	-818.94	-11.67	-398.47	-7.12
27	-196.30	-3.40	-294.75	-5.78	-618.21	-8.19	-192.78	-3.30
28	133.42	1.97	-573.71	-13.05	-483.21	-6.90	-	-
29	-	-	-517.19	-12.23	57.53	.73	-	-
30	-	-	-975.89	-20.46	173.54	2.14	-	-
31	-	-	119.76	2.15	131.85	1.73	-	-
Av.	514.07	7.97	210.36	4.33	796.00	11.40	652.40	12.87

Table 60. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Actual Input Data and Actual Load Factor

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-178.35	-2.72	194.60	4.15	355.95	4.36	-943.10	-19.62
2	180.17	2.99	633.42	11.45	593.35	7.22	-837.78	-18.19
3	366.85	5.94	754.39	13.89	597.20	7.30	-386.12	-6.80
4	362.64	5.31	-25.62	-.49	667.13	8.11	-347.59	-5.89
5	160.15	2.46	-370.71	-7.24	486.98	5.94	-496.75	-8.23
6	169.20	2.62	-494.03	-9.72	158.53	2.08	-293.38	-5.26
7	162.32	2.35	-394.70	-8.74	166.42	2.24	-24.75	-.48
8	304.53	4.28	-439.11	-10.13	357.46	4.09	243.30	5.06
9	-94.92	-1.29	-816.43	-15.79	136.17	1.55	-387.18	-8.58
10	-240.51	-3.30	-780.88	-14.88	145.70	1.83	132.38	2.48
11	-98.08	-1.31	-150.91	-2.93	-82.00	-.92	370.62	6.62
12	-81.33	-1.22	-12.47	-.25	-167.14	-2.42	-156.25	-2.69
13	-98.27	-1.50	138.04	2.76	-307.84	-6.12	-427.44	-7.11
14	128.94	1.84	268.62	5.72	-616.11	-13.29	259.11	4.96
15	-186.66	-2.77	613.18	12.79	-693.93	-11.98	180.46	3.83
16	-173.72	-2.61	502.41	9.19	-534.15	-8.48	469.61	10.22
17	-78.98	-1.24	-66.06	-1.26	-474.66	-6.51	583.84	10.83
18	-329.45	-5.04	-21.35	-.42	-319.99	-4.15	336.49	6.13
19	-178.24	-3.10	127.75	2.51	279.18	3.29	1176.29	21.11
20	-308.77	-5.65	526.44	9.93	233.01	2.67	1371.74	24.33
21	-459.63	-7.36	319.89	6.40	589.77	7.84	1157.27	20.89
22	-3.55	-.06	-152.76	-3.25	802.17	8.53	735.86	14.81
23	276.42	4.64	825.23	14.46	946.73	11.92	-24.85	-.52
24	145.74	2.31	683.20	12.84	492.46	6.69	-145.07	-2.66
25	110.62	1.69	373.17	7.15	279.87	3.96	1212.04	21.29
26	182.52	2.89	326.65	6.17	-219.41	-3.13	985.57	17.62
27	-20.89	-.36	-448.36	-8.79	-267.30	-3.54	1501.87	25.68
28	292.04	4.32	-702.58	-15.99	-169.90	-2.43	-	-
29	-	-	-466.99	-11.05	-67.18	-.85	-	-
30	-	-	-908.90	-19.06	-191.33	-2.36	-	-
31	-	-	343.40	6.17	123.89	1.62	-	-
Av.	191.91	2.97	415.56	8.24	371.71	5.08	562.47	10.44

Table 61. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Predicted Input Data and Actual Load Factor

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-477.29	-7.28	-496.72	-10.60	749.09	9.18	-771.68	-16.06
2	-794.01	-13.19	-324.21	-5.86	817.94	9.96	-896.19	-19.46
3	-832.80	-13.50	337.92	6.22	661.11	8.08	-382.65	-6.74
4	13.83	.20	96.36	1.86	480.28	5.84	-288.84	-4.89
5	469.08	7.21	-121.36	-2.37	417.87	5.09	90.29	1.50
6	914.60	14.15	-356.02	-7.01	-101.93	-1.34	103.95	1.86
7	513.38	7.43	-379.57	-8.41	-243.75	-3.28	-355.67	-6.90
8	391.04	5.50	-519.63	-11.98	717.67	8.22	-926.26	-19.26
9	915.86	12.42	-392.69	-7.60	733.20	8.36	-681.90	-15.11
10	572.41	7.86	-404.16	-7.70	-153.46	-1.93	-735.27	-13.76
11	152.67	2.04	-378.95	-7.37	703.05	7.88	-613.44	-10.95
12	483.20	7.25	-203.63	-4.01	-894.56	-12.93	-481.18	-8.29
13	678.94	10.38	-109.77	-2.19	-2072.08	-41.22	445.16	7.41
14	565.11	8.06	-60.84	-1.30	-2300.82	-49.62	-17.10	-.33
15	-344.57	-5.11	134.55	2.81	-2343.36	-40.46	-637.43	-13.52
16	-613.25	-9.23	-141.07	-2.58	-2015.48	-31.99	-949.27	-20.66
17	-458.47	-7.19	-12.30	-.24	-405.94	-5.57	-266.00	-4.93
18	-912.00	-13.94	28.62	.57	-891.71	-11.56	-490.62	-8.94
19	-688.90	-11.98	-5.51	-.11	1780.66	20.95	-889.09	-15.96
20	-629.29	-11.52	217.39	4.10	2671.73	30.60	-599.47	-10.63
21	-744.72	-11.93	187.17	3.75	1512.94	20.11	615.54	11.11
22	-781.57	-12.65	-151.30	-3.22	1924.06	20.46	-209.54	-4.22
23	-740.78	-12.43	-91.10	-1.60	1033.06	13.01	-442.89	-9.19
24	-363.70	-5.76	-56.91	-1.07	-365.74	-4.97	-460.13	-8.45
25	47.88	.73	182.02	3.49	-973.44	-13.76	-279.54	-4.91
26	306.35	4.85	116.14	2.19	-1495.82	-21.31	-33.92	-.61
27	160.22	2.78	-223.56	-4.38	-1356.14	-17.96	-56.41	-.96
28	329.95	4.88	-643.88	-14.65	-135.06	-1.93	-	-
29	-	-	-659.80	-15.61	-683.98	-8.68	-	-
30	-	-	-1055.68	-22.14	122.59	1.51	-	-
31	-	-	-147.11	-2.64	133.88	1.75	-	-
Av.	532.00	8.27	265.68	5.47	996.53	14.18	471.09	9.13

Table 62. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Univariate Model and Average Load Fcator

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	204.60	3.12	-73.35	-1.57	547.84	6.71	-815.25	-16.96
2	-575.62	-9.56	156.76	2.83	-24.11	-.29	-553.71	-12.02
3	95.52	1.55	158.69	2.92	103.72	1.27	751.03	13.23
4	739.29	10.82	-245.40	-4.73	101.82	1.24	122.97	2.08
5	-351.37	-5.40	-214.97	-4.20	171.49	2.09	96.18	1.59
6	70.73	1.09	-174.56	-3.43	-352.10	-4.62	-514.72	-9.23
7	88.87	1.29	-259.50	-5.75	-102.40	-1.38	-693.06	-13.44
8	122.99	1.73	-257.71	-5.94	1276.27	14.62	-769.85	-16.01
9	595.94	8.08	-12.07	-.23	332.52	3.79	-653.61	-14.49
10	269.14	3.70	-103.84	-1.98	-500.22	-6.29	436.78	8.17
11	-89.65	-1.20	-27.17	-.53	1017.85	11.41	51.75	.92
12	-664.23	-9.97	-193.99	-3.82	-1526.56	-22.07	41.75	.72
13	-99.69	-1.52	-160.31	-3.20	-2207.56	-43.91	51.45	.86
14	146.90	2.10	-124.34	-2.65	-1112.09	-23.98	-926.88	-17.74
15	-520.95	-7.73	237.98	4.96	423.67	7.31	-908.22	-19.26
16	192.71	2.90	123.13	2.25	52.23	.83	-532.15	-11.58
17	-132.94	-2.08	-226.58	-4.33	751.19	10.30	450.27	8.35
18	-241.97	-3.70	-227.96	-4.50	543.97	7.05	-144.11	-2.63
19	-338.12	-5.88	-170.62	-3.35	717.85	8.45	-114.36	-2.05
20	-422.40	-7.73	67.37	1.27	450.08	5.15	-127.25	-2.26
21	185.65	2.97	-81.19	-1.63	-696.28	-9.26	-322.89	-5.83
22	81.93	1.33	-297.58	-6.34	1770.93	18.83	-868.25	-17.47
23	-50.18	-.84	369.06	6.47	-629.83	-7.93	-563.57	-11.69
24	147.03	2.33	-253.83	-4.77	-782.38	-10.62	265.62	4.88
25	99.72	1.52	-208.50	-4.00	-442.14	-6.25	2.72	.05
26	-152.52	-2.41	-101.64	-1.92	-115.47	-1.64	-270.84	-4.84
27	-532.70	-9.23	-404.06	-7.92	510.42	6.76	-15.86	-.27
28	661.01	9.78	-547.25	-12.45	-208.67	-2.98	-	-
29	-	-	-299.66	-7.09	761.19	9.66	-	-
30	-	-	-528.89	-11.09	234.53	2.90	-	-
31	-	-	759.87	13.65	-193.14	-2.53	-	-
Av.	281.23	4.34	227.99	4.57	601.95	8.46	409.82	8.10

Table 63. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Models with Actual Input Data and Average Load Factor

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	47.55	.73	224.87	4.80	39.53	.48	-983.87	-20.47
2	141.32	2.35	563.04	10.18	276.79	3.37	-204.35	-4.44
3	598.65	9.70	341.12	6.28	62.46	.76	195.51	3.44
4	374.80	5.49	-491.20	-9.48	288.37	3.51	-52.71	-.89
5	6.59	.10	-510.96	-9.98	128.51	1.57	-278.02	-4.61
6	53.41	.83	-376.34	-7.41	-138.02	-1.81	-134.48	-2.41
7	85.47	1.24	-307.23	-6.81	54.66	.73	-74.31	-1.44
8	334.27	4.70	-267.67	-6.17	380.68	4.36	124.38	2.59
9	95.34	1.29	-689.78	-13.34	34.87	.40	-637.24	-14.12
10	-274.52	-3.77	-468.19	-8.92	42.50	.53	373.77	7.00
11	-315.62	-4.22	64.48	1.25	138.55	1.55	245.12	4.38
12	-473.23	-7.10	-111.24	-2.19	-385.99	-5.58	-486.38	-8.38
13	-380.04	-5.81	-4.86	-.10	-627.96	-12.49	-427.17	-7.11
14	-86.57	-1.23	162.12	3.45	-727.72	-15.69	328.99	6.30
15	-83.27	-1.24	552.88	11.53	-383.96	-6.63	-117.87	-2.50
16	29.88	.45	231.70	4.24	-57.50	-.91	289.22	6.29
17	-183.23	-2.87	-366.17	-7.00	144.55	1.98	221.95	4.12
18	-124.28	-1.90	-197.73	-3.90	-110.80	-1.44	-87.36	-1.59
19	-258.48	-4.49	-70.90	-1.39	577.59	6.80	877.14	15.74
20	-462.17	-8.46	338.94	6.39	343.46	3.93	476.92	8.46
21	-249.16	-3.99	39.53	.79	221.36	2.94	115.85	2.09
22	319.49	5.17	-367.66	-7.83	883.90	9.40	-223.12	-4.49
23	317.42	5.33	825.21	14.46	72.26	.91	-614.62	-12.75
24	168.31	2.66	152.23	2.86	-423.97	-5.76	-210.17	-3.86
25	85.27	1.30	-121.61	-2.33	-108.68	-1.54	1255.69	22.05
26	81.29	1.29	30.45	.57	-284.90	-4.06	92.67	1.66
27	-248.31	-4.30	-661.70	-12.97	300.83	3.98	752.25	12.86
28	522.74	7.73	-681.49	-15.51	40.51	.58	-	-
29	-	-	-318.36	-7.53	59.79	.76	-	-
30	-	-	-658.36	-13.80	139.81	1.73	-	-
31	-	-	717.36	12.89	229.09	3.00	-	-
Av	228.60	3.56	352.11	6.98	248.70	3.52	365.97	6.89

Table 64. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Model with Predicted Input and Average Load Factor Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	127.37	1.94	135.68	2.90	-468.57	-5.74	-315.41	-6.56
2	-739.21	-12.28	341.82	6.18	267.26	3.25	-767.94	-16.68
3	238.42	3.86	616.82	11.36	124.55	1.52	505.56	8.91
4	880.03	12.88	2.65	.05	-5.30	-.06	5.39	.09
5	223.19	3.43	-478.09	-9.34	399.87	4.88	-12.03	-.20
6	335.70	5.19	-452.05	-8.90	-229.04	-3.01	-780.36	-13.99
7	114.03	1.65	-439.81	-9.74	-164.19	-2.21	-404.20	-7.84
8	371.66	5.23	-325.73	-7.51	854.20	9.78	39.88	.83
9	1090.75	14.79	-118.06	-2.28	198.44	2.26	57.58	1.28
10	268.82	3.69	-658.56	-12.55	-868.80	-10.92	-227.71	-4.26
11	-457.70	-6.12	-338.14	-6.58	1476.91	16.56	326.42	5.83
12	-403.52	-6.06	-76.84	-1.51	-2158.80	-31.21	214.21	3.69
13	-155.46	-2.38	-85.24	-1.70	-1078.06	-21.45	-181.31	-3.02
14	-90.13	-1.29	36.84	.78	-202.31	-4.36	-1234.93	-23.64
15	-316.09	-4.69	482.02	10.05	-332.27	-5.74	297.61	6.31
16	-221.36	-3.33	405.61	7.42	-48.56	-.77	107.10	2.33
17	-424.76	-6.66	-89.76	-1.72	1153.56	15.82	649.40	12.04
18	-556.54	-8.51	-397.32	-7.84	-723.24	-9.37	-121.19	-2.21
19	-582.13	-10.12	-145.97	-2.87	1661.86	19.56	-96.23	-1.73
20	-676.11	-12.37	173.14	3.26	1141.60	13.07	726.88	12.89
21	-430.64	-6.90	232.24	4.65	-1133.76	-15.07	645.10	11.64
22	-104.89	-1.70	-216.45	-4.61	1494.04	15.89	-354.31	-7.13
23	26.84	.45	209.90	3.68	-943.76	-11.89	-122.59	-2.54
24	354.00	5.60	295.86	5.56	-658.50	-8.94	-320.16	-5.88
25	228.87	3.49	114.59	2.20	-417.80	-5.91	-106.05	-1.86
26	179.30	2.84	-38.03	-.72	-50.37	-.72	859.76	15.37
27	-228.47	-3.96	-290.13	-5.69	666.06	8.82	282.43	4.83
28	467.23	6.91	-846.16	-19.25	119.48	1.71	-	-
29	-	-	-498.49	-11.79	-283.02	-3.59	-	-
30	-	-	-605.51	-12.70	618.74	7.64	-	-
31	-	-	563.24	10.12	74.83	.98	-	-
Av.	367.62	5.65	313.25	6.31	645.73	8.47	361.55	6.80

Table 65. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Univariate Model and Average Load Fcator

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-44.79	-.68	-339.58	-7.25	721.43	8.84	-1175.45	-24.46
2	-678.69	-11.28	-185.33	-3.35	811.83	9.88	-1316.87	-28.60
3	-546.66	-8.86	76.96	1.42	712.96	8.72	-448.22	-7.90
4	107.81	1.58	-67.49	-1.30	685.78	8.34	-235.19	-3.98
5	72.69	1.12	-196.56	-3.84	658.95	8.03	-104.63	-1.73
6	287.40	4.45	-222.00	-4.37	132.11	1.73	-549.67	-9.86
7	503.49	7.29	-355.66	-7.88	-88.38	-1.19	-967.67	-18.76
8	624.08	8.78	-399.52	-9.21	977.63	11.20	-1181.67	-24.57
9	979.55	13.28	-298.64	-5.78	1077.52	12.28	-1410.46	-31.26
10	945.40	12.99	-296.02	-5.64	246.12	3.09	-829.29	-15.52
11	799.23	10.68	-185.37	-3.61	1238.80	13.89	-616.63	-11.01
12	52.16	.78	-221.05	-4.36	-743.33	-10.75	-455.67	-7.85
13	-18.91	-.29	-187.62	-3.75	-2479.53	-49.32	-182.73	-3.04
14	265.17	3.78	-137.93	-2.94	-2837.85	-61.20	-889.29	-17.02
15	-54.98	-.82	193.17	4.03	-2034.66	-35.13	-1276.68	-27.07
16	-179.25	-2.70	203.14	3.72	-1532.00	-24.31	-1321.98	-28.77
17	-494.19	-7.75	-82.88	-1.58	-342.98	-4.70	-712.93	-13.22
18	-532.79	-8.14	-247.38	-4.88	-110.42	-1.43	-679.69	-12.39
19	-1064.10	-18.50	-196.90	-3.87	1102.17	12.97	-653.10	-11.72
20	-1238.48	-22.67	80.40	1.52	1866.89	21.38	-642.23	-11.39
21	-634.66	-10.17	83.35	1.67	792.92	10.54	-586.52	-10.59
22	-484.83	-7.85	-225.92	-4.81	2360.36	25.10	-1012.45	-20.38
23	-612.93	-10.29	246.85	4.32	792.38	9.98	-1107.35	-22.97
24	-267.38	-4.23	-6.39	-.12	-7.85	-.11	-680.83	-12.50
25	11.14	.17	-89.77	-1.72	-518.75	-7.34	-450.37	-7.91
26	12.42	.20	-35.43	-.67	-750.02	-10.68	-572.69	-10.24
27	-430.60	-7.46	-356.37	-6.99	-195.28	-2.59	-347.18	-5.94
28	369.78	5.47	-753.66	-17.15	-534.20	-7.63	-	-
29	-	-	-699.74	-16.55	8.12	.10	-	-
30	-	-	-948.82	-19.90	372.68	4.60	-	-
31	-	-	80.17	1.44	139.28	1.82	-	-
Av.	439.77	6.87	248.39	5.15	866.87	12.54	755.83	14.84

Table 66. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Models with Actual Input Data and Average Load Factor

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	47.55	.73	332.38	7.10	145.29	1.78	-1044.77	-21.74
2	141.32	2.35	648.36	11.72	621.67	7.57	-836.49	-18.16
3	598.65	9.70	628.87	11.58	540.88	6.61	-364.12	-6.42
4	374.80	5.49	-140.13	-2.70	748.52	9.10	-290.08	-4.91
5	6.59	.10	-524.57	-10.25	617.88	7.53	-495.99	-8.22
6	53.41	.83	-550.45	-10.83	222.29	2.92	-466.84	-8.37
7	85.47	1.24	-534.04	-11.83	158.31	2.13	-275.19	-5.34
8	334.27	4.70	-452.30	-10.43	465.31	5.33	157.03	3.27
9	95.34	1.29	-891.90	-17.25	266.66	3.04	-461.95	-10.24
10	-274.52	-3.77	-845.46	-16.11	125.38	1.58	103.96	1.95
11	-315.62	-4.22	-292.36	-5.69	217.85	2.44	338.92	6.05
12	-473.23	-7.10	-179.79	-3.54	-446.08	-6.45	-224.16	-3.86
13	-380.04	-5.81	-9.38	-.19	-728.68	-14.50	-533.49	-8.88
14	-86.57	-1.23	227.53	4.85	-996.67	-21.49	31.82	.61
15	-83.27	-1.24	677.04	14.12	-945.34	-16.32	49.17	1.04
16	29.88	.45	508.12	9.30	-601.02	-9.54	443.61	9.65
17	-183.23	-2.87	-136.62	-2.61	-286.16	-3.92	512.78	9.51
18	-124.28	-1.90	-229.08	-4.52	-443.41	-5.75	289.68	5.28
19	-258.48	-4.49	-81.22	-1.60	344.32	4.05	1125.18	20.20
20	-462.17	-8.46	398.75	7.52	599.28	6.86	1282.86	22.75
21	-249.16	-3.99	284.23	5.69	462.72	6.15	1011.30	18.25
22	319.49	5.17	-223.07	-4.75	1379.53	14.67	567.19	11.41
23	317.42	5.33	753.82	13.21	654.01	8.24	-125.79	-2.61
24	168.31	2.66	533.37	10.02	349.46	4.74	-243.99	-4.48
25	85.27	1.30	198.32	3.80	281.55	3.98	1160.46	20.38
26	81.29	1.29	205.60	3.88	-155.75	-2.22	851.59	15.22
27	-248.31	-4.30	-511.73	-10.03	137.46	1.82	1390.78	23.78
28	522.74	7.73	-887.20	-20.19	-218.76	-3.12	-	-
29	-	-	-647.60	-15.32	-117.38	-1.49	-	-
30	-	-	-882.15	-18.50	16.98	.21	-	-
31	-	-	305.43	5.49	131.33	1.72	-	-
Av.	228.60	3.56	442.61	8.86	433.09	6.04	543.67	10.10

Table 67. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy Transfer Function Models with Predicted Input Data and Average Load Fcator

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-241.37	-3.68	-337.73	-7.21	549.04	6.73	-870.32	-18.11
2	-839.35	-13.95	-306.35	-5.54	845.42	10.29	-894.88	-19.43
3	-553.10	-8.96	201.23	3.71	605.26	7.40	-360.67	-6.35
4	26.65	.39	-15.47	-.30	563.67	6.86	-231.87	-3.93
5	323.00	4.97	-268.22	-5.24	549.94	6.70	90.98	1.51
6	812.52	12.57	-411.04	-8.09	-35.95	-.47	-57.76	-1.04
7	440.53	6.38	-518.49	-11.49	-252.32	-3.39	-622.10	-12.06
8	420.40	5.91	-533.04	-12.29	820.89	9.40	-1034.63	-21.51
9	1080.37	14.65	-462.82	-8.95	854.67	9.74	-761.18	-16.87
10	542.08	7.45	-464.70	-8.85	-174.56	-2.19	-768.42	-14.38
11	-57.67	-.77	-526.50	-10.24	976.75	10.95	-651.11	-11.62
12	124.10	1.86	-377.23	-7.43	-1202.14	-17.38	-552.79	-9.52
13	430.17	6.58	-264.70	-5.29	-2632.10	-52.36	353.48	5.88
14	363.26	5.18	-104.99	-2.24	-2803.43	-60.46	-257.03	-4.92
15	-238.83	-3.54	205.72	4.29	-2658.70	-45.90	-792.39	-16.80
16	-396.53	-5.97	-134.61	-2.46	-2096.84	-33.28	-984.21	-21.42
17	-568.84	-8.92	-82.15	-1.57	-219.12	-3.01	-349.61	-6.48
18	-689.43	-10.54	-177.08	-3.50	-1023.90	-13.27	-544.94	-9.93
19	-776.04	-13.49	-220.10	-4.33	1833.90	21.58	-964.22	-17.31
20	-791.21	-14.48	81.45	1.54	2932.90	33.59	-729.42	-12.94
21	-525.30	-8.41	150.50	3.01	1402.81	18.65	451.53	8.15
22	-417.87	-6.76	-221.59	-4.72	2426.12	25.80	-415.88	-8.37
23	-692.44	-11.62	-175.92	-3.08	743.95	9.37	-552.54	-11.46
24	-339.26	-5.37	-230.66	-4.33	-526.59	-7.15	-564.61	-10.36
25	22.28	.34	.27	.01	-971.44	-13.74	-348.29	-6.12
26	207.16	3.28	-10.03	-.19	-1420.94	-20.24	-197.54	-3.53
27	-60.09	-1.04	-284.37	-5.58	-895.01	-11.85	-207.33	-3.54
28	559.30	8.27	-826.37	-18.80	-183.69	-2.62	-	-
29	-	-	-847.83	-20.05	-738.07	-9.37	-	-
30	-	-	-1028.25	-21.56	323.01	3.99	-	-
31	-	-	-188.65	-3.39	141.32	1.85	-	-
Av.	447.83	6.98	311.55	6.43	1077.56	15.47	541.10	10.50

Table 68. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Univariate Models

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	204.60	3.12	-34.29	-.73	513.47	6.29	-666.33	-13.86
2	-575.62	-9.56	230.46	4.17	43.28	.53	-485.81	-10.55
3	95.52	1.55	107.67	1.98	94.52	1.16	750.16	13.22
4	739.29	10.82	-255.09	-4.92	120.18	1.46	107.13	1.81
5	-351.37	-5.40	-323.75	-6.33	144.95	1.77	54.71	.91
6	70.73	1.09	-222.01	-4.37	-393.58	-5.17	-515.28	-9.24
7	88.87	1.29	-174.24	-3.86	-122.16	-1.64	-565.50	-10.96
8	122.99	1.73	-249.44	-5.75	1278.76	14.64	-573.69	-11.93
9	595.94	8.08	-95.83	-1.85	299.15	3.41	-581.06	-12.88
10	269.14	3.70	-174.48	-3.32	-539.47	-6.78	492.60	9.22
11	-89.65	-1.20	-114.47	-2.23	1024.10	11.48	74.47	1.33
12	-664.23	-9.97	-225.74	-4.45	-1613.39	-23.33	67.98	1.17
13	-99.69	-1.52	-248.71	-4.97	-2121.60	-42.20	102.20	1.70
14	146.90	2.10	-132.25	-2.82	-976.87	-21.07	-851.44	-16.30
15	-520.95	-7.73	203.65	4.25	539.89	9.32	-720.57	-15.28
16	192.71	2.90	89.01	1.63	125.35	1.99	-422.63	-9.20
17	-132.94	-2.08	-314.41	-6.01	770.65	10.57	473.64	8.78
18	-241.97	-3.70	-333.18	-6.58	490.36	6.35	-82.02	-1.49
19	-338.12	-5.88	-266.70	-5.24	754.20	8.88	-75.70	-1.36
20	-422.40	-7.73	38.38	.72	430.03	4.92	-77.12	-1.37
21	185.65	2.97	-35.65	-.71	-805.91	-10.71	-232.20	-4.19
22	81.93	1.33	-294.16	-6.27	1813.42	19.28	-725.21	-14.59
23	-50.18	-.84	326.60	5.72	-809.15	-10.19	-406.52	-8.43
24	147.03	2.33	-392.12	-7.37	-679.56	-9.23	345.78	6.35
25	99.72	1.52	-347.46	-6.66	-394.71	-5.58	77.62	1.36
26	-152.52	-2.41	-188.52	-3.56	-116.00	-1.65	-220.39	-3.94
27	-532.70	-9.23	-429.05	-8.41	491.44	6.51	109.96	1.88
28	661.01	9.78	-590.13	-13.43	-324.56	-4.63	-	-
29	-	-	-339.28	-8.02	775.97	9.85	-	-
30	-	-	-632.32	-13.26	249.69	3.08	-	-
31	-	-	654.82	11.76	-253.71	-3.32	-	-
Av.	281.23	4.34	260.12	5.21	616.45	8.61	365.10	7.16

Table 69. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Transfer Function Models with Actual Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	44.42	.68	267.92	5.72	12.29	.15	-858.25	-17.86
2	68.05	1.13	490.73	8.87	438.46	5.34	-228.44	-4.96
3	585.03	9.48	352.26	6.49	46.15	.56	2.83	.05
4	379.50	5.55	-308.70	-5.95	261.75	3.18	-110.37	-1.87
5	15.24	.23	-513.91	-10.04	-1.73	-.02	-118.06	-1.96
6	133.60	2.07	-218.15	-4.29	-86.77	-1.14	-75.59	-1.36
7	88.89	1.29	-337.45	-7.48	-10.97	-.15	-31.86	-.62
8	366.99	5.16	-269.37	-6.21	445.33	5.10	235.61	4.90
9	66.09	.90	-685.69	-13.27	-204.04	-2.33	-471.62	-10.45
10	-178.19	-2.45	-424.99	-8.10	171.33	2.15	573.63	10.74
11	-360.67	-4.82	90.19	1.75	-230.96	-2.59	344.34	6.15
12	-582.81	-8.75	13.91	.27	-236.13	-3.41	-471.68	-8.12
13	-455.20	-6.96	35.93	.72	-291.96	-5.81	-377.02	-6.27
14	-60.55	-.86	322.13	6.86	-668.32	-14.41	341.84	6.54
15	-150.65	-2.23	542.07	11.30	-322.63	-5.57	-119.49	-2.53
16	.61	.01	237.89	4.35	-117.75	-1.87	370.32	8.06
17	-97.65	-1.53	-363.65	-6.95	40.94	.56	225.54	4.18
18	-99.28	-1.52	-114.30	-2.26	-117.98	-1.53	29.60	.54
19	-272.52	-4.74	118.43	2.33	750.67	8.83	1205.26	21.63
20	-522.61	-9.56	506.54	9.55	-46.50	-.53	571.13	10.13
21	-422.10	-6.76	127.77	2.56	328.61	4.37	157.46	2.84
22	239.12	3.87	-354.31	-7.55	429.22	4.56	-201.24	-4.05
23	381.46	6.40	863.19	15.12	306.33	3.86	-338.26	-7.02
24	186.88	2.96	289.88	5.45	-204.13	-2.77	27.23	.50
25	152.10	2.32	26.65	.51	-121.51	-1.72	1242.50	21.82
26	100.93	1.60	149.87	2.83	-478.14	-6.81	104.80	1.87
27	-310.81	-5.38	-560.19	-10.98	55.27	.73	815.36	13.94
28	394.63	5.84	-703.57	-16.01	-35.95	-.51	-	-
29	-	-	-200.94	-4.75	217.42	2.76	-	-
30	-	-	-501.99	-10.53	176.77	2.18	-	-
31	-	-	744.18	13.37	-36.93	-.48	-	-
Av.	239.88	3.75	346.35	6.85	222.35	3.10	357.38	6.70

Table 70. One-Day Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Transfer Function Models with Predicted Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	92.13	1.40	184.46	3.94	-541.40	-6.64	-151.26	-3.15
2	-740.54	-12.31	232.36	4.20	347.73	4.23	-709.29	-15.40
3	208.40	3.38	588.67	10.84	135.81	1.66	456.73	8.05
4	874.12	12.79	162.41	3.13	15.33	.19	-107.49	-1.82
5	225.08	3.46	-412.16	-8.05	357.71	4.36	-77.30	-1.28
6	339.07	5.24	-319.92	-6.30	-301.04	-3.95	-682.72	-12.24
7	148.98	2.16	-416.19	-9.22	-163.63	-2.20	-245.69	-4.76
8	373.05	5.25	-370.45	-8.54	846.20	9.69	189.22	3.93
9	1103.20	14.96	-71.57	-1.38	174.26	1.99	94.30	2.09
10	257.37	3.54	-563.09	-10.73	-965.94	-12.14	-113.96	-2.13
11	-416.01	-5.56	-318.91	-6.20	1524.07	17.09	420.69	7.51
12	-420.11	-6.31	19.27	.38	-2365.23	-34.20	278.97	4.80
13	-197.03	-3.01	-4.76	-.10	-944.58	-18.79	-131.16	-2.18
14	-121.46	-1.73	140.52	2.99	-13.63	-.29	-1152.82	-22.07
15	-305.45	-4.53	502.03	10.47	-201.27	-3.47	437.47	9.28
16	-248.87	-3.75	390.55	7.15	14.35	.23	134.18	2.92
17	-437.01	-6.85	-72.66	-1.39	1139.78	15.63	663.57	12.31
18	-518.42	-7.92	-310.85	-6.14	-835.83	-10.83	-65.08	-1.19
19	-572.43	-9.95	1.32	.03	1712.62	20.15	-30.08	-.54
20	-681.99	-12.48	330.42	6.23	1151.45	13.19	921.33	16.34
21	-458.25	-7.34	299.04	5.99	-1363.18	-18.12	747.72	13.50
22	-172.23	-2.79	-225.51	-4.80	1604.35	17.06	-234.26	-4.71
23	-6.15	-.10	286.49	5.02	-1298.31	-16.35	-16.04	-.33
24	381.82	6.04	358.39	6.73	-434.85	-5.90	-169.25	-3.11
25	236.69	3.61	304.96	5.85	-336.60	-4.76	46.61	.82
26	205.35	3.25	99.21	1.87	-67.30	-.96	865.91	15.48
27	-220.69	-3.82	-224.32	-4.40	599.85	7.94	394.80	6.75
28	440.74	6.52	-822.28	-18.71	-64.16	-.92	-	-
29	-	-	-410.23	-9.70	-247.39	-3.14	-	-
30	-	-	-478.83	-10.04	668.86	8.26	-	-
31	-	-	629.24	11.31	10.24	.13	-	-
Av.	371.52	5.72	308.10	6.19	659.58	8.53	353.26	6.62

Table 71. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Univariate Models

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-44.79	-.68	-320.53	-6.84	721.43	8.84	-1146.16	-23.85
2	-678.69	-11.28	-226.25	-4.09	811.83	9.88	-1301.04	-28.25
3	-546.66	-8.86	4.48	.08	712.96	8.72	-415.52	-7.32
4	107.81	1.58	-113.75	-2.19	685.78	8.34	-207.41	-3.51
5	72.69	1.12	-233.07	-4.55	658.95	8.03	-85.18	-1.41
6	287 40	4.45	-221.51	-4.36	132.11	1.73	-520.11	-9.33
7	503.49	7.29	-379.64	-8.41	-88.38	-1.19	-937.15	-18.17
8	624.08	8.78	-438.84	-10.12	977.63	11.20	-1167.02	-24.27
9	979.55	13.28	-267.75	-5.18	1077.52	12.28	-1410.64	-31.26
10	945.40	12.99	-290.18	-5.53	246.12	3.09	-832.40	-15.58
11	799.23	10.68	-123.04	-2.39	1238.80	13.89	-624.59	-11.15
12	52.16	.78	-193.12	-3.81	-743.33	-10.75	-455.79	-7.85
13	-18.91	-.29	-244.18	-4.88	-2479.53	-49.32	-157.45	-2.62
14	265.17	3.78	-143.09	-3.05	-2837.85	-61.20	-848.59	-16.24
15	-54.98	-.82	236.17	4.92	-2034.66	-35.13	-1261.02	-26.74
16	-179.25	-2.70	243.45	4.46	-1532.00	-24.31	-1309.51	-28.50
17	-494.19	-7.75	-31.08	-.59	-342.98	-4.70	-708.32	-13.14
18	-532.79	-8.14	-228.54	-4.51	-110.42	-1.43	-674.51	-12.29
19	-1064.10	-18.50	-144.78	-2.85	1102.17	12.97	-643.29	-11.55
20	-1238.48	-22.67	85.47	1.61	1866.89	21.38	-627.94	-11.14
21	-634.66	-10.17	104.99	2.10	792.92	10.54	-547.87	-9.89
22	-484.83	-7.85	-207.49	-4.42	2360.36	25.10	-988.54	-19.89
23	-612.93	-10.29	297.61	5.21	792.38	9.98	-1102.16	-22.87
24	-267.38	-4.23	54.46	1.02	-7.85	-.11	-668.28	-12.27
25	11.14	.17	-33.90	-.65	-518.75	-7.34	-442.62	-7.77
26	12.42	.20	-18.09	-.34	-750.02	-10.68	-562.74	-10.06
27	-430.60	-7.46	-385.79	-7.56	-195.28	-2.59	-329.34	-5.63
28	369.78	5.47	-755.74	-17.20	-534.20	-7.63	-	-
29	-	-	-676.82	-16.01	8.12	.10	-	-
30	-	-	-867.98	-18.20	372.68	4.60	-	-
31	-	-	160.19	2.88	139.28	1.82	-	-
Av.	439.77	6.87	249.42	5.16	866.87	12.54	739.82	14.54

Table 72. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Transfer Function Models with Actual Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	44.42	.68	335.42	7.16	101.89	1.25	-876.36	-18.23
2	68.05	1.13	652.52	11.80	690.15	8.40	-803.00	-17.44
3	585.03	9.48	648.21	11.94	560.68	6.86	-516.01	-9.09
4	379.50	5.55	-23.45	-.45	710.38	8.64	-440.80	-7.47
5	15.24	.23	-526.11	-10.28	511.49	6.24	-464.39	-7.69
6	133.60	2.07	-459.99	-9.05	279.38	3.67	-382.81	-6.87
7	88.89	1.29	-550.39	-12.19	137.05	1.84	-300.02	-5.82
8	366.99	5.16	-529.83	-12.22	517.70	5.93	59.45	1.24
9	66.09	.90	-942.58	-18.24	95.80	1.09	-452.49	-10.03
10	-178.19	-2.45	-859.89	-16.39	240.36	3.02	299.78	5.61
11	-360.67	-4.82	-299.53	-5.83	-106.74	-1.20	572.98	10.23
12	-582.81	-8.75	-120.94	-2.38	-301.73	-4.36	-54.56	-.94
13	-455.20	-6.96	-21.25	-.42	-422.62	-8.41	-359.15	-5.98
14	-60.55	-.86	319.41	6.81	-979.77	-21.13	144.41	2.76
15	-150.65	-2.23	690.00	14.39	-1048.17	-18.10	-52.20	-1.11
16	.61	.01	558.11	10.21	-805.55	-12.78	328.42	7.15
17	-97.65	-1.53	-104.85	-2.00	-506.13	-6.94	328.49	6.09
18	-99.28	-1.52	-162.80	-3.21	-462.45	-5.99	160.69	2.93
19	-272.52	-4.74	42.44	.83	472.52	5.56	1337.00	24.00
20	-522.61	-9.56	525.50	9.91	297.52	3.41	1500.38	26.61
21	-422.10	-6.76	366.87	7.34	584.80	7.77	1207.49	21.80
22	239.12	3.87	-186.37	-3.97	949.09	10.09	661.16	13.31
23	381.46	6.40	775.70	13.59	910.80	11.47	42.81	.89
24	186.88	2.96	638.75	12.00	534.64	7.26	75.35	1.38
25	152.10	2.32	315.82	6.05	284.99	4.03	1285.20	22.57
26	100.93	1.60	292.45	5.52	-343.70	-4.90	848.74	15.17
27	-310.81	-5.38	-431.55	-8.46	-161.73	-2.14	1339.47	22.90
28	394.63	5.84	-902.60	-20.54	-263.67	-3.76	-	-
29	-	-	-610.70	-14.44	7.62	.10	-	-
30	-	-	-799.91	-16.77	82.08	1.01	-	-
31	-	-	383.32	6.89	-42.86	-.56	-	-
Av.	239.88	3.75	454.11	9.07	432.71	6.06	551.62	10.20

Table 73. One-Week Lead Time Daily Peak Forecast Error Using Daily Energy and Load Factor Transfer Function Models with Predicted Input Data

DAY	FEBRAURY		MAY		AUGUST		OCTOBER	
	MW	%	MW	%	MW	%	MW	%
1	-241.25	-3.68	-356.03	-7.60	548.95	6.73	-796.41	-16.57
2	-839.32	-13.95	-356.51	-6.44	845.33	10.29	-857.74	-18.63
3	-552.98	-8.96	137.75	2.54	605.07	7.40	-280.58	-4.94
4	26.84	.39	42.95	.83	563.58	6.86	-168.68	-2.86
5	322.88	4.96	-247.61	-4.84	549.94	6.70	143.88	2.38
6	812.41	12.57	-312.24	-6.14	-36.14	-.47	-13.07	-.23
7	440.33	6.38	-479.57	-10.62	-252.32	-3.39	-585.62	-11.35
8	420.35	5.91	-611.76	-14.11	821.09	9.40	-1027.89	-21.37
9	1080.25	14.65	-476.35	-9.22	854.67	9.74	-772.29	-17.12
10	542.03	7.45	-402.83	-7.68	-174.56	-2.19	-770.84	-14.43
11	-57.64	-.77	-477.84	-9.29	976.65	10.95	-637.70	-11.38
12	124.13	1.86	-317.63	-6.26	-1202.24	-17.38	-522.94	-9.01
13	430.34	6.58	-232.40	-4.64	-2632.10	-52.36	396.20	6.59
14	363.29	5.18	-40.04	-.85	-2803.43	-60.46	-196.35	-3.76
15	-238.79	-3.54	221.08	4.61	-2658.80	-45.90	-761.46	-16.15
16	-396.58	-5.97	-102.13	-1.87	-2096.95	-33.28	-947.80	-20.63
17	-568.64	-8.91	-52.38	-1.00	-219.02	-3.00	-340.84	-6.32
18	-689.48	-10.54	-97.29	-1.92	-1024.12	-13.27	-556.11	-10.13
19	-776.25	-13.50	-129.41	-2.54	1834.15	21.58	-974.89	-17.50
20	-791.33	-14.48	161.90	3.05	2933.26	33.59	-724.15	-12.84
21	-525.27	-8.41	180.31	3.61	1403.11	18.65	498.26	8.99
22	-417.99	-6.77	-262.10	-5.58	2426.38	25.80	-381.19	-7.67
23	-692.49	-11.62	-182.28	-3.19	744.04	9.37	-523.72	-10.87
24	-339.07	-5.37	-199.42	-3.75	-526.69	-7.15	-519.71	-9.54
25	22.31	.34	105.59	2.02	-971.24	-13.73	-312.26	-5.48
26	207.12	3.28	99.29	1.87	-1420.94	-20.24	-167.37	-2.99
27	-60.21	-1.04	-224.38	-4.40	-895.32	-11.86	-213.32	-3.65
28	559.04	8.27	-817.34	-18.60	-183.51	-2.62	-	-
29	-	-	-830.08	-19.63	-738.60	-9.37	-	-
30	-	-	-1009.27	-21.16	323.40	4.00	-	-
31	-	-	-108.81	-1.95	141.41	1.85	-	-
Av.	447.81	6.98	299.18	6.19	1077.64	15.47	521.90	10.13

The vita has been removed from
the scanned document